Overview of AI-Enabled Forest Monitoring and Conservation Framework

Maddhigalla Lakshumaiah and D. S. Rao *
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Hyderabad, India
Email: lakshumaiah@klh.edu.in (M.L.), dsrao@klh.edu.in (D.S.R.)

Manuscript received January 16, 2026; revised February 26, 2026; revised again March 20, 2026; accepted April 19, 2026
*Corresponding author

***Abstract*—Forest monitoring has become increasingly difficult as pressures from land-use change, climate variability, and illegal activities continue to grow. Much of the existing monitoring still depends on field surveys and manual interpretation, which are costly and hard to maintain over large or remote forest areas. Because of these limitations, artificial intelligence has been explored in recent years as a supporting tool for forest conservation. This paper brings together recent studies that use Artificial Intelligence (AI) for forest-related applications. The work reviewed includes satellite- and UAV-based change detection, wildlife monitoring using camera traps and acoustic sensors, and predictive models used to assess deforestation, fire risk, and illegal activities. The article also explains how these approaches are integrated with sensor networks, edge computing, and cloud platforms. Looking into the reviewed studies, it has been identified that AI is employed to automate the analysis of the collected information as well as to manage large amounts of ecological information. Even though the performance of AI has been enhanced compared to the existing methods, there are still challenges that have not been addressed. These include the reliance on regional datasets, the lack of evaluation of AI performance in realistic deployment settings, and the restrictions of real-world infrastructures. The ethical considerations have been addressed, but there is no uniform treatment of these issues. Overall, the current literature suggests a complementary role of AI technology within a comprehensive forest governance system.**

***Index Terms*—artificial intelligence, conservation decision support, deforestation prediction, forest monitoring, IoT and edge computing, remote sensing, wildlife and biodiversity assessment**

I. Introduction

Forests provide fundamental ecosystem services, such as the conservation of biodiversity, carbon sequestration, regulation of the water cycle, and protection of soils, as well as playing a very significant role in climate change mitigation. Conversely, forest ecosystems face mounting threats from deforestation, degradation, climate change, insect attacks, and forest fires. The main factors contributing to these stresses are land-use change, agricultural expansion, and the unsustainable extraction of forest resources. Recent trends confirm that the synergies of human and climate-induced stresses have amplified the resilience of forests, which poses a significant threat to biodiversity and climate resilience [1].

Traditional methods of monitoring and conserving forests are primarily dependent on field monitoring, statistical analysis, and professional expertise. Though these methods work well in small spatial settings, they prove to be rather expensive, time-consuming, and challenging to implement in a large or intractable forest region. In addition to this, these methods do not support near-real-time monitoring or prognostic analysis, thus restricting the ability to react instantaneously to any impending danger in the form of illicit tree falling, diseases, or rapid land use/land cover changes in the forest ecosystem [2].

Artificial Intelligence (AI) has emerged as a promising approach to address these challenges. It enables autonomous analysis and large-scale monitoring of forest environments. Machine learning and deep learning algorithms combined with satellite, drone, and LiDAR imagery data demonstrated enhanced performance for forest disturbance detection, vegetation mapping, and species distribution identification. Recent research has shown that AI approaches to modeling work particularly well for the complex spatial-temporal analysis of high-resolution remote sensing data [3]. Deep learning strategies were found to achieve superior performance on vegetation segmentation and tree type classification from LiDAR data, as well as deforestation patterns identification from aerial imagery data through the use of convolutional neural networks [3]. Similar AI-driven geoinformatics approaches have been applied to agricultural phenology monitoring under climate variability, demonstrating the value of integrated satellite and machine learning analysis for ecosystem dynamics understanding [4]. Fig. 1 illustrates a conceptual representation demonstrating the integration of AI techniques to devise a forest monitoring aid.

In parallel to these efforts, the rising focus on edge computing, IoT-based sensing, and data automation has led to near-real-time forest monitoring and a quicker flow of data between forest monitoring systems and decision-makers. These emerging trends slowly bring forest conservation into a data-savvy and adaptive management approach, where AI is harnessed for early warning and intervention [1]. Despite such efforts, some important areas related to the availability of data, degrees of model applicability to different forest environments, evaluation criteria, and ethics involved with large-scale natural environment monitoring still pose important hurdles to

doi: 10.18178/ijeetc.15.4.276-287

broader adoption [6]. This article presents a narrative review of existing research involving AI for forest monitoring and conservation, synthesizing integrated AI-enabled monitoring frameworks rather than proposing a novel algorithm. The review compiles state-of-the-art capabilities, comparative system components, existing challenges, and emerging integration patterns across recent studies, while outlining future research directions for responsible forest conservation.

Compared with earlier survey papers that typically focus on individual AI techniques or specific monitoring modalities, this review emphasizes system-level integration across sensing, analytics, and conservation decision infrastructures. The manuscript also consolidates emerging edge–cloud architectures, conservation platforms, and predictive decision-support systems, thereby providing a holistic perspective on operational AI-enabled forest monitoring ecosystems.

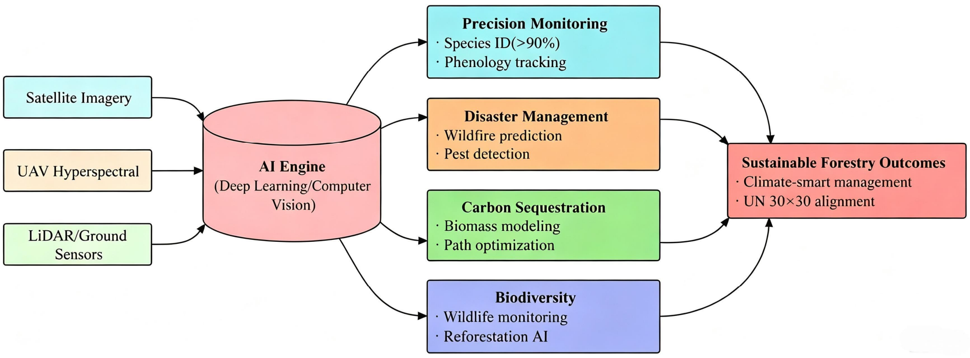

Fig. 1. Conceptual framework illustrating the interaction between sensing technologies, AI analytics, communication infrastructure, and conservation decision processes in AI-enabled forest monitoring systems [5].

Literature Identification Approach

Although this work is presented as a narrative review, studies were identified through structured searches conducted across Scopus, Web of Science, and Google Scholar databases. The search focused on publications between 2020 and 2025 using keyword combinations including "AI forest monitoring," "wildlife acoustic monitoring," "deforestation prediction," and "conservation edge computing." Inclusion criteria comprised peer-reviewed journal and conference articles emphasizing artificial intelligence applications in forest or biodiversity monitoring. Studies primarily describing conventional remote sensing without AI components were excluded. This approach supports transparency while maintaining the flexibility characteristic of narrative reviews.

In addition to studying identification, a qualitative assessment approach was adopted to ensure the relevance and reliability of the included literature. Studies were evaluated based on (i) methodological clarity, (ii) relevance to AI-driven forest monitoring or conservation, (iii) type and quality of data used, and (iv) reported validation or performance evaluation. Rather than applying a formal scoring system, the review emphasizes comparative interpretation of methods, data sources, and application contexts. This approach aligns with the narrative review framework while providing a structured basis for synthesizing findings across heterogeneous studies.

II. Artificial Intelligence in Forest and Natural Resource Conservation

A. Remote Sensing-Based AI Approaches

Remote sensing has emerged as a mainstream method for forest and natural resource monitoring over vast areas. The integration of artificial intelligence, satellite data, and aerial data allows for the automated interpretation of subtle spatiotemporal relationships, enabling the detection of ecological change, forest morphology, and associated land use change. These technologies are emerging as efficient alternatives for situation monitoring through ground truthing, especially for areas with restricted ground truthing capacity.

B. Satellite Imagery

Satellite data continues to be a fundamental aspect of forest mapping because of its spatial and temporal resolution. AI-based classification of satellite data has enhanced the accuracy of land cover change detection, including deforestation, fragmentation, and degradation. Gu and Zeng carried out a study on the application of AI in satellite remote sensing for land cover change detection and concluded that supervised, as well as unsupervised, machine learning algorithms are efficient for the analysis of multi-temporal data on a regional and global level. The study illustrates the need for a model that has the ability to handle the variability of spectral and temporal inconsistency of satellite data, which plays a critical role in forest and natural resource management [7].

The Convolutional Neural Network (CNN) has been used extensively for classifying forest cover and land use, often performing more accurately than traditional machine learning methods. Similar deep learning approaches applied to satellite imagery for crop yield estimation further demonstrate the effectiveness of CNN-based vegetation monitoring across agricultural and forest ecosystems [8]. Long-term analysis using satellite data for land use/land cover change in India, covering the period 1990 to 2024, revealed a significant destruction of forests due to anthropogenic factors, establishing the effectiveness of AI technology for environmental analysis at a macro level. The integration of multi-temporal satellite data with change detection analysis using a CNN has further made possible an update of land use/land cover maps, enabling a sensitivity to spatial change useful for forest resource mapping [9]. The remote sensing technology platform and its classification based on scales are represented in Fig. 2.

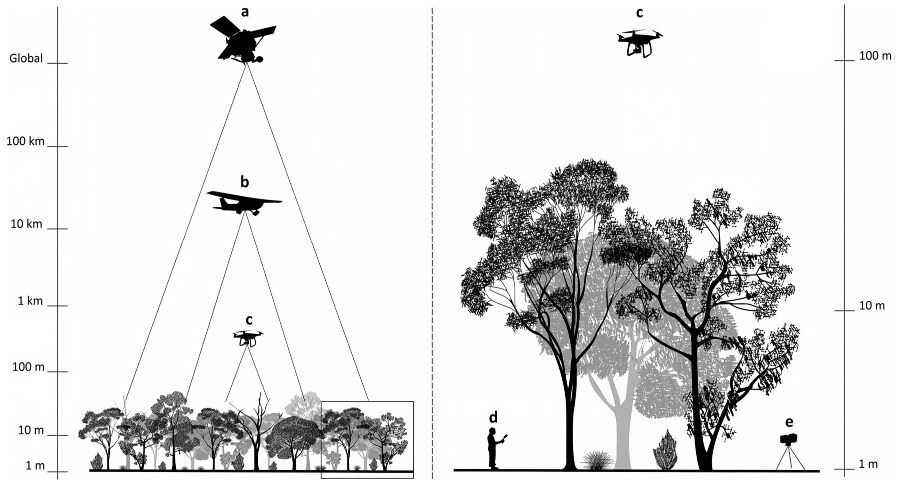

Fig. 2. Remote sensing platforms across spatial scales, ranging from satellite and airborne systems to UAVs and ground-based laser scanners for forest data acquisition [10].

1) Drone-based monitoring

Unmanned Aerial Vehicles (UAVs) offer high-resolution imagery that can be used to detect structural patterns in forests that are not easily detected by satellite imagery. Artificial intelligence developed for UAV data can be used for tree crown boundary extraction, dead tree detection, and habitat mapping, each helping in forest condition assessments that can measure biodiversity. Recent advancements in deep learning have increased the efficiency of segmentation and object detection in aerial images for heterogeneous forests [11]. The use of self-attention mechanisms in the U-Net model has led to improved dead tree detection in complex canopy structures for forest health assessments [11].

The use of monitoring systems based on UAVs that employ multiple sensors, such as RGB and infrared images, with deep learning algorithms enables constant monitoring of human activities and environmental dynamics. This clearly shows that drones have the ability to ensure adaptive forest resource management practices [12].

Compared with satellite-based monitoring, UAV-based approaches provide substantially higher spatial resolution and structural detail, enabling fine-scale assessments such as individual tree health analysis and canopy damage detection. However, satellite systems offer superior temporal continuity and regional coverage at lower operational cost. Consequently, recent studies increasingly adopt hybrid workflows where satellite imagery supports large-scale change screening while UAV observations enable targeted validation and localized ecological assessment.

2) Land use change detection

Land-Use and Land-Cover (LULC) change detection represents a key application of AI-driven remote sensing in forest conservation. Machine learning applied to satellite time series data enables classification and quantification of land transitions, such as the conversion of forested areas to agricultural or urban land. CNN-based LULC classification has been shown to improve spatial precision in change detection, supporting conservation planning and policy evaluation [7, 9].

Beyond single-sensor analysis, the integration of multi-source remote sensing data with AI models has improved the assessment of forest degradation linked to biotic and climatic stressors. Machine learning applied to Sentinel-2 and Google Earth imagery has enabled the identification of degraded forest stands and estimation of both the density and spatial extent of damage, indicating suitability for near-operational monitoring applications [13].

C. Acoustic and Bioacoustic AI Systems

1) Wildlife monitoring

Acoustic methods are now commonly used in wildlife monitoring because they allow animal activity to be recorded without direct monitoring. In forest environments, traditional survey methods depend heavily on field visits and visual identification, which are difficult to carry out over large areas and long periods. However, such methods are also manpower intensive and tend to disturb wildlife, especially in environmentally sensitive habitats. Another method of acoustic monitoring is passive acoustic monitoring.

There are also recent studies showing that machine learning models trained using acoustic data are more reliable than analyses done manually, particularly if the acoustic data contains background noises of wind, insects, and rain. In addition to spectral representation, other studies also incorporate simple context information, such as the time of recording and location of the sensors, during training of the models. This enhances the reliability of species detection, particularly those that call less and at low levels of intensity and distances. These studies illustrate the applicability and limitations of acoustic AI systems [14].

Acoustic data are also utilized for analyzing soundscapes rather than animal species. In this approach, more than one species is monitored at the same time, while the variation in overall calls is analyzed. In these techniques, it is possible to investigate seasonal variations as well as long-term trends, in addition to the potential reactions to environmental modifications. In dense forests or in isolated areas where monitoring with cameras is not possible, analyzing soundscapes can be a feasible monitoring process for acquiring ecological data. Most existing studies focus on specific animal groups, such as birds or amphibians, but similar approaches are gradually being explored for other taxa. Overall, current evidence suggests that AI-based acoustic monitoring can support biodiversity assessment while reducing the need for continuous fieldwork [15, 16].

2) Illegal logging and poaching detection

In addition to ecological monitoring, acoustic analysis has been explored for identifying illegal human activities in forest areas. Illegal logging, in particular, produces characteristic sounds such as chainsaw operation and tree cutting, which can be captured by passive acoustic sensors. These sensors can be deployed across forest regions that are difficult to patrol regularly. The recorded audio is then analysed using machine learning models trained to separate human-generated sounds from natural background noise. A typical acoustic monitoring workflow that integrates local edge inference with cloud-based analysis to support real-time alerts for enforcement agencies is displayed in Fig. 3.

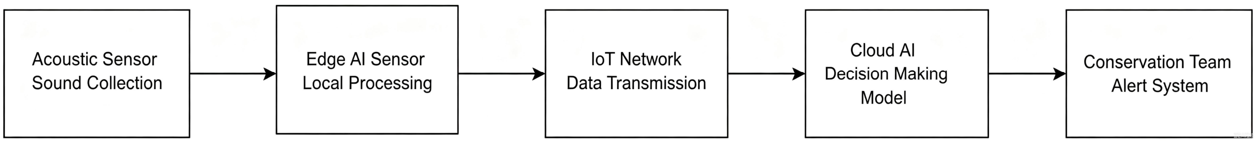

Fig. 3. Acoustic monitoring workflow showing sensor deployment, local preprocessing, machine learning inference, cloud aggregation, and alert dissemination to enforcement stakeholders.

Studies focusing on logging detection typically use standard audio features combined with supervised classification methods. Algorithms such as support vector machines and multilayer perceptrons have been reported to distinguish chainsaw sounds from environmental noise under a range of recording conditions. While performance varies depending on sensor placement and background noise levels, the results indicate that acoustic monitoring can provide early indications of logging activity in areas where physical inspection is delayed or infrequent [17].

Across acoustic monitoring studies, a recurring pattern is the trade-off between detection sensitivity and environmental noise robustness. While machine learning classifiers demonstrate promising performance under controlled acoustic conditions, real-world deployments frequently encounter overlapping biological and anthropogenic sound sources that degrade classification reliability. Additionally, the majority of studies focus on proof-of-concept detection tasks rather than long-term autonomous monitoring, leaving questions regarding sensor maintenance, data transmission reliability, and sustained model performance largely unexplored. These observations indicate that acoustic AI research is transitioning from algorithmic validation toward operational resilience challenges.

Research on AI-based detection of poaching-related sounds is more limited in the peer-reviewed literature. However, existing work on forest acoustic monitoring suggests that gunshots, vehicle engines, and other human-related sounds can be identified as anomalous events within natural soundscapes. Some studies propose linking such detection systems to alert mechanisms so that forest officials can respond more quickly. This approach is particularly relevant for protected areas where continuous visual monitoring is not possible. Modifications of the composition of the soundscapes have also been mentioned as an indirect indicator of the presence of more people. This lends evidence for acoustic monitoring being a useful method for the protection of the forests [15].

3) AI for wildlife monitoring and biodiversity assessment

- Camera traps

Camera traps are widely adopted in the study of wildlife since they enable constant monitoring of the subjects without disturbing them. They are especially applicable in forests where conducting surveys directly could be expensive or challenging. A disadvantage with these devices, however, is the enormous number of photographs collected, some of which are without wildlife or are repeat observations of the same species. Analyzing the data manually is laborious.

To counter this challenge, AI techniques are being employed increasingly for the analysis of camera trap photographs by cameras. Many research pieces opt for a two-step method that first identifies animals in photographs, followed by the identification of the species type. Object detection algorithms are known to be reasonably robust against realistic situations such as changing lighting conditions, vegetation cover, and noisy backgrounds. The algorithms are useful for eliminating mistakes caused by a dataset with a skewed distribution of species, which tend to be major in image collections [18]. The accuracy rate improves compared to previous semi-automatic techniques.

CNNs and ensemble classifiers have also been employed for the classification of detected animal species. They work effectively for commonly spotted animal species and require less human involvement in processing large datasets. This makes AI-assisted camera traps more suitable for monitoring animal populations over a wider range of space and time intervals [19]. This is because repetitive classification activity is minimized with AI-assisted camera traps compared to manual camera traps.

- Species Identification

Species identification is one of the main components of biodiversity monitoring and population analysis. Manual identification of species from camera trap images is a complex task that becomes harder as the size of the database increases. In addition, it is prone to human biases, particularly for species with similarities in appearance. Classifier systems using deep learning techniques have been integrated to minimize these drawbacks.

From past studies, it can be determined that deep neural networks are able to recognize species correctly as long as they are trained adequately on a diversity of images. Even when images have restrictions such as partial occlusion, lack of contrast, or blurriness, current methods can analyze species correctly. Recent analysis has highlighted the application of models, including ResNet-based models and transformers, for species classification [20] for multiple species, depending upon the habitat.

Some of these studies also make use of contextual information simultaneously with image information. Use of data such as the time of image capture or the type of habitat can aid in the classification of images and can avoid confusion in cases where images are of closely related species [21]. Ensemble learning can also tackle the challenges of imbalance in classifications as well as image similarity, with stable results for common species while flagging uncertain instances for human evaluation [19].

- Habitat Analysis

AI techniques are also utilized for the analysis of habitat traits and biodiversity patterns, which are not limited to species levels. Machine learning algorithms and deep learning algorithms are employed to detect land cover patterns and habitat classification on satellite images and UAV mapping. The techniques are employed for the analysis of ecosystem patterns to identify regions of habitat degradation or fragmentation.

Research has also shown that it is more accurate to create habitat maps when multiple sources of remote sensing data are used, as well as for analyzing relationships between wildlife and habitats [22]. This is especially true for habitats such as wetlands, as even small changes in spatial distribution have a great influence on habitats [22].

Deep semantics for segmentation serve to support the fine-scale mapping for habitat characteristic determination. Such models enable the analysis of habitat suitability as well as spatial distribution patterns for species. Analysis for habitat suitability with data on species occurrence can serve to support conservation planning. Habitat-scale analysis with AI, thus, can support camera trap surveys as well as species determination research on an ecological scale [23].

Biodiversity monitoring studies collectively highlight the growing shift from single-species detection toward ecosystem-level inference through multi-modal AI analysis. However, persistent dataset imbalance and geographic bias remain critical constraints, as most camera trap datasets are concentrated in well-studied conservation regions. Consequently, models demonstrating high benchmark accuracy may exhibit degraded performance in underrepresented habitats or rare-species scenarios. This discrepancy underscores the need for collaborative dataset development initiatives and uncertainty-aware classification frameworks capable of supporting human expert validation in conservation workflows.

III. AI-Based Predictive and Decision-Support Systems

A. Deforestation and Forest Degradation Prediction

Deforestation and forest degradation prediction are also a crucial part of proactive forest management because, through such prediction, the conservation efforts can be planned to mitigate the damage. The classic remote sensing technique is mostly retrospective because it deals with the regions where the forest degradation has already taken place. Although such tools are useful, they provide very little assistance regarding the decision-making that is done in advance. On the other hand, the use of remote sensing along with machine learning and deep learning is aimed at predicting the factors related to the forest cover change. It is shown that the past studies provide evidence that the stability in the prediction regarding the forest region can be achieved.

1) ML and DL models used

A variety of ML models have been applied to deforestation prediction, typically using satellite image time series together with environmental and geographic variables. Ensemble-based methods, particularly Random Forest (RF) and gradient boosting models such as eXtreme Gradient Boosting (XGBoost), are among the most frequently reported approaches. Their performance is often attributed to their ability to handle nonlinear relationships and mixed data types. For example, a study examining forest cover change along the Iraq–Turkey border evaluated several ML models using Sentinel-2 imagery in combination with climatic and topographic variables. XGBoost achieved the best overall performance, with R^2 values above 0.90 and relatively low RMSE, and its outputs were further analysed using SHapley Additive exPlanations (SHAP) to interpret the influence of individual predictors [24].

Neural network-based approaches have also been explored, particularly when temporal dynamics are of interest. Hybrid models that combine multilayer perceptrons (MLPs) with Long Short-Term Memory (LSTM) networks have been used to capture both spatial variation and temporal trends in deforestation time series. Applications in the Amazon region show that these hybrid structures are better suited to representing space–time interactions than models that rely solely on static spatial inputs or sequential data alone [25].

More recently, Convolutional Neural Networks (CNNs) designed for semantic segmentation, along with transformer-inspired architectures, have been used to extract spatial features related to land cover change. Even though these models are used mainly for change detection at a pixel level, their representation capabilities can also be used for prediction purposes to detect repeating spatial patterns for forest degradation [26].

2) Input data types

The performance of deforestation models in predicting forest loss is also largely dependent on data selection and quality used in the model. Satellite data is generally central in most predictive models since it has adequate coverage spatially and in terms of the time dimension. Optical satellite images such as Sentinel-2 and Landsat are most appropriate since that data has multispectral layers that can be used in estimating vegetation indicator variables such as NDVI [25].

In addition to spectral values, topographic variables like elevation and gradient, and climatic conditions like rainfall and temperature, are often included in prediction models. These variables represent the conditions of the environment and affect the stability of a forest. In the report on the area surveyed at the borders of the Iran and Turkey region, it was noticed that climatic values dominated the initial periods of changes in forests, while values related to the activities of the residents started playing a more dominant part in the latter periods [24].

The temporal features that are derived from multi-year satellite data enable models to handle seasonal dynamics, slow change, as well as sudden changes in forest coverage. The application of time-related inputs to recurrent neural networks, including LSTM, has been effective in these models, handling long-term dynamics as opposed to models that utilize satellite images from a single date [27].

In order to enhance the transparency of results, some research has made use of the SHAP interpretability technique to evaluate the importance of factors in the model. The results have demonstrated that the relative importance of factors like road construction and exposure of soil heightens with time, while the effects of climatic factors assume more prominence in the initial stages of the transition process in the forests [24].

Predictive modeling literature demonstrates increasing methodological sophistication through hybrid architectures and explainable AI integration. Nevertheless, predictive validity remains closely tied to data availability and regional context, limiting model portability across heterogeneous forest ecosystems. The predominance of retrospective satellite-derived predictors also raises concerns regarding the delayed representation of socio-economic drivers influencing forest change. These factors collectively indicate that future predictive frameworks should incorporate socio-environmental covariates, adaptive retraining strategies, and cross-regional benchmarking to enhance decision-support reliability.

B. AI for Risk Assessment and Resource Optimization

Assessing risk is becoming more common in forest management, especially in areas where a lack of resources is an obstacle to enforcing control over forests. Risks such as poaching, logging, and fires are spatiotemporally variable, meaning forest protection authorities are forced to make certain decisions without the whole picture in view. More recently, artificial intelligence has been employed in forest protection for the purpose of using past data, together with environmental data, to point out where these threats are more likely to occur.

1) Hotspot detection

A common use of AI in conservation is the identification of locations that experience a higher frequency of illegal or harmful activities. Most studies rely on past incident data, such as recorded poaching events or logging detections, combined with environmental variables including terrain, land cover, and distance to roads or settlements. Machine learning models are trained on these datasets to estimate the probability of future incidents across the landscape. Compared with traditional statistical approaches, machine learning models are better able to capture complex spatial relationships and temporal repetition in incident data. Recent studies applying deep learning techniques have reported improved prediction of poaching risk when spatial and temporal information is explicitly incorporated into the model. The resulting outputs are typically presented as risk maps that indicate areas where monitoring and enforcement efforts may be prioritised [28].

Patrol-based datasets have also been used to generate risk surfaces for hotspot detection. In these cases, patrol outcomes are analysed alongside environmental predictors to identify areas where illegal activities are more likely to be encountered. Such risk maps are used to guide monitoring strategies and to support decisions on where sensors or camera traps may be deployed to increase the likelihood of detection [29].

3) Patrol planning

After the identification of the higher-risk zones, the next step is concerned with the allocation of the patrol resources. With the help of artificial intelligence in the process of patrol planning, optimizing routes based on the performance level can be achieved. In this process, the system does not promote designing routes, but it assists by considering the level of risks with optimization methods.

Several trials have found that patrol plans based on risk prediction models can improve the efficiency of detection. By allocating patrols to the region of relatively high risk, the model was found to be successful in increasing the discovery of snares and other signs of illegal activities compared to routine allocations. Field tests conducted on protected parks show that AI-enhanced patrol plans can improve patrol efficiency without adding to the workload [30].

Some recent studies have also assessed strategies where the local community is taken along, together with the forest rangers. These models rely on the use of risk prediction to allocate patrol efforts to the groups. This strategy was suggested as a means to improve enforcement efforts as well as the incorporation of the local community in conservation efforts [31].

4) Fire risk prediction

Fire outbreaks are also a significant source of risks within the forest ecosystems and are dependent on environmental factors as well as human interventions. Fire prediction is a critical job undertaken by conservation and land management organizations. Several machine learning models have been extensively used for this purpose on the basis of inputs related to climate, topography, and vegetation indices obtained from remote sensing technologies.

Studies conducted for inter-model comparison, exploring decision trees, random forests, support vector machine algorithms, and neural networks, have shown that nonlinear relationships that affect fire occurrences can be well captured using models based on AI algorithms [32, 33]. Variables like temperature, rainfall, slope, vegetation density, and fuel measures have been identified as key inputs in these models.

In practice, fire risk prediction models are used to support planning rather than to provide exact forecasts. Outputs of the AI models involve the development of risk maps that identify areas where preventive measures may be required or where resources must be positioned in advance of high-risk periods. These outputs, if combined with a Geographic Information System platform, can be used to support operational planning and enhance preparedness in regions prone to wildfire events.

IV. Integration of AI with Emerging Technologies

A. IoT-Enabled Forest Monitoring

The Internet of Things (IoT) has brought about significant changes in the monitoring of the forest through constant tracking of environmental parameters over a vast region [34]. Sensors are organized in a network for monitoring temperature, humidity, soil moisture, air quality, and acoustic signals to give a better insight into the forest dynamics that could hardly be measured through ground-level monitoring. Fig. 4 represents an AI-edge-IoT framework for monitoring forest health.

Such systems facilitate the early indication of irregularities such as forest fires, insect invasions, and ecosystem stress. Through the acquisition of high-resolution information on microclimates, sap flow, and carbon transport, Internet of Things sensors facilitate near-real-time evaluation that can enhance the efficacy of conservation actions [34].

The Internet of Forest Things (IoFT) extends this capability even further through the fusion of data from ground sensors, drones, weather stations, and other disparate sources. This creates a greater coverage area and a continuous data flow that makes it easier to identify illicit logging and habitat deterioration, and other human-caused threats at a varied scale [34].

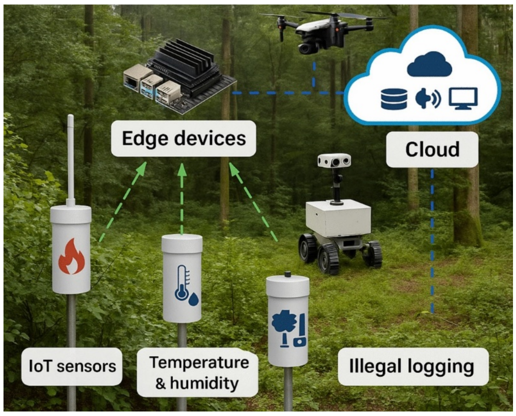

Fig. 4. AI–edge IoT systems in forest monitoring [1].

In spite of these advantages, extending IoT networks to remote forests is difficult. This is due to limitations imposed by energy consumption, communication, or device diversity. Solutions to these issues include designing sensors to consume little power, using long-range communication methods such as LoRaWAN, as well as standardized data models for seamless interaction among devices [34].

Edge processing

Cloud-based data processing can pose a limitation in remote forest regions because of latency, as well as fluctuating connectivity [1]. The edge computing system averts these challenges since it can process data locally, ensuring rapid reaction to an emergency, as well as preventing the transfer of irrelevant data [1].

The Lightweight AI models could perform the inference operation on the nodes of the sensors. Methods such as Pruning & Quantization allow these models to run efficiently on power-constrained hardware, with sufficient accuracy [1]. This has many applications in anomaly detection or early warning systems, like unusual rises in temperature, warning of a possible fire hazard, & unusual sound patterns of human intrusions.

The running of the edge-enabled network will be made possible by energy-aware scheduling and adaptive data aggregation. These techniques will help the system balance processing and communication while optimizing energy use, making the system always responsive for a prolonged period of time [1].

Reported edge computing deployments indicate trade-offs between latency reduction, energy consumption, and model complexity. Lightweight convolutional and transformer-lite models achieve millisecond-scale inference suitable for early warning scenarios but may sacrifice classification robustness under noisy conditions. Conversely, transmitting raw data to cloud infrastructure improves analytical fidelity but increases latency and communication energy cost. Consequently, hybrid edge–cloud partitioning strategies are increasingly proposed to balance throughput, responsiveness, and power efficiency.

B. Cloud and Platform-Based Conservation Systems

The evolution of cloud computing and analytical platforms has changed conservation research with regard to handling geospatial data. Cloud computing allows for the use of platforms scalable enough to conduct remote sensing analysis with different sources of data. It offers efficient ways of analyzing different sources of remote sensing data. It is even very effective for monitoring and change analysis.

1) Google Earth Engine

Google Earth Engine (GEE) is a cloud-based geospatial big data computation platform with an extensive inventory of satellite observation data, including long-term series data for sensors such as Landsat and Sentinel satellites. The capacity for satellite data processing using distributed computing infrastructure provides researchers with the capacity for environmental analyses over a wide geographic area without necessarily needing high-performance computing infrastructure for localized analyses. Several studies indexed in Scopus confirmed the role of GEE in forest and ecosystem change analyses through the application of algorithms based on satellite data for land cover change, tree loss, and degradation measurements.

For instance, a current study used GEE, along with optical satellite data from Sentinel-2 satellites and radar satellite data from Sentinel-1, for forest degradation mapping in a biosphere reserve, measuring two periods of forest vegetation loss due to climatic disturbances using cloud-based platforms with high spatial resolution [35]. The application of GEE for environmental monitoring, including forests, has numerous potential applications in environmental monitoring using cloud-based platforms [36–38].

Apart from the detection of forest change, the scalability of the Earth Engine can also be utilized for advanced spatial planning that can help conservation experts identify areas of priority to be protected. A 2025 study utilized GEE to create interactive applications that allow the visualization of land cover change and help to identify conservation priorities through spatially explicit trends [36].

Using GEE for the assessment of ecosystems highlights the usefulness of the GEE model as a cloud computing analytical infrastructure in conservation biology. Indeed, the use of GEE in conservation biology provides a vast amount of data, including computation, for the evaluation processes associated with environmental change [36].

2) Conservation platforms: SMART and similar tools

In complement to cloud-based geospatial platforms such as GEE, there are decision-support systems specifically devised for conservation that are becoming more prominent for protected area management and enforcement planning. Of these, the Spatial Monitoring and Reporting Tool (SMART) is one of the tools widely accepted in the global conservation sector. SMART is a software solution for managers to have a systematic approach to the collection, storage, analysis, and reporting of the observations made in the field with respect to wildlife, threats, or the results of patrolling activities. It enables the managers to make decisions through the use of visual representations of spatial patterns of biodiversity indicators or threats, simpler forms of threat reporting, and the ability to choose activities for implementation. Although there are few published studies in the Scopus-indexed database on the analytical capabilities of SMART, its contribution towards the homogenization of monitoring approaches in protected conservation zones has been recognized in the conservation sector for adaptive management of these zones [37].

In the real-world setting, the SMART system functions as a conservation data service that links data gathering on the ground to analytical and reporting tools designed for management-level users. In the optimal implementation of the tool, the software provides the ground-level team and management with the ability to understand the patterns of illegitimate acts, species records, and patrol area coverage, which inform resource allocation and subsequent enforcement decisions [38].

Recent conservation literature also emphasizes that such integrated analytical platforms, examples of which include SMART, further reduce the cost of monitoring while providing greater ecological insight when scaled into other observational data. Integrated modeling frameworks, for example, have combined ranger patrol data with systematic surveys and camera trap records to provide improved occupancy estimates at reduced operational costs, thereby showcasing structured data platforms' value in realizing sound conservation monitoring [39]. Fig. 5 gives an exemplary outline of how AI, IoT sensing, and cloud-based platforms are commonly integrated in forest monitoring systems reported in the literature.

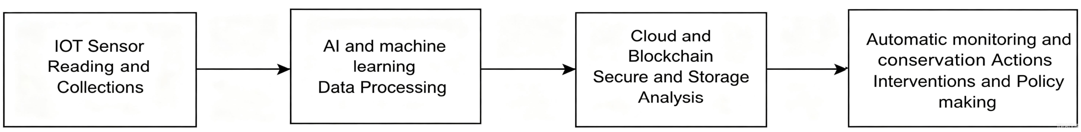

Fig. 5. Schematic representation of components and data flow in AI-enabled forest monitoring systems.

Despite growing interest in integrated monitoring ecosystems, the reviewed literature reveals that true end-to-end implementations remain relatively scarce. Many studies report individual components, such as sensing, analytics, or decision-support platforms, without a comprehensive evaluation of system interoperability and lifecycle performance. Challenges, including heterogeneous data formats, communication constraints, and governance considerations, hinder seamless integration across monitoring layers. Consequently, advancing AI-enabled forest monitoring will likely depend less on isolated algorithmic innovation and more on systems engineering approaches emphasizing modularity, interoperability standards, and stakeholder-centered deployment evaluation. Integration across sensing modalities and analytical pipelines remains an emerging research direction. Recent studies demonstrate that combining acoustic sensors, camera traps, satellite imagery, and patrol data within unified analytical frameworks can enhance ecological inference and enforcement effectiveness. However, challenges related to data standardization, synchronization, and interoperability persist, limiting seamless cross-modal integration in operational deployments.

V. Comparative Analysis of Existing Studies

A. *Summary of Existing Studies*

The literature reviewed above shows diverse applications of artificial intelligence in forest monitoring, biodiversity assessment, prediction modelling, and decision support applications. The literature studies vary greatly in their analysis aims, extent, data, and system integration levels. Table I provides a compilation of various Scopus-indexed literature studies covered under review, categorized based on application type, data type, methodologies used, and their main results, to facilitate a comprehensive understanding.

Methods using remote sensing technologies have been preferring large-scale forest monitoring, especially regarding land use/cover change mapping and forest degradation analysis. Ecological surveys, acoustic sensors, and camera-trap technologies are more interested in niche ecological assessments, enforcement issues, and other minute details, while forecasting models could help in active forest fire, deforestation, and illegitimate activity prediction. The current trend of IoT, Edge, and cloud integration indicates a move from research to application.

TABLE I: Comparative Analysis of AI-Based Approaches in Forest Monitoring and Conservation

Application domain	Data sources	AI techniques	Key strengths	Key limitations	Refs.
Forest cover and LULC change detection	Satellite imagery (Landsat, Sentinel, PlanetScope), time-series data	CNNs, supervised and unsupervised ML	Scalable monitoring over large regions; improved detection of gradual and abrupt land-use change	Sensitivity to cloud cover and spectral variability; limited local context	[6–8]
UAV-based forest condition assessment	High-resolution UAV imagery, RGB, and infrared data	CNNs, U-Net variants, object detection	Fine-scale structural detail; effective detection of dead trees and canopy stress	Limited spatial coverage; higher operational cost	[9, 10]
Forest degradation assessment	Multi-source satellite data, climatic indicators	ML, data fusion methods	Improved detection of biotic and climatic stress-related degradation	Requires careful data fusion and calibration	[11]
Acoustic wildlife monitoring	Passive acoustic recordings, contextual metadata	Deep learning classifiers, soundscape analysis	Non-invasive monitoring; suitable for dense or inaccessible forests	Noise sensitivity; limited taxonomic coverage	[12–14]
Illegal logging detection	Acoustic sensor data	SVMs, MLPs, anomaly detection	Early detection of logging activity; low dependence on visual monitoring	False positives in noisy environments; sparse long-term validation	[15]
Camera trap-based wildlife monitoring	Camera trap images, metadata	CNNs, ensemble classifiers	High accuracy for common species; reduced manual annotation effort	Class imbalance: lower accuracy for rare species	[16, 17]
Species identification	Camera trap images, contextual metadata	Deep neural networks, ensemble models	Robust classification under challenging imaging conditions	Requires large, diverse training datasets	[18, 19]
Habitat and biodiversity assessment	Satellite and UAV imagery, species occurrence data	ML, DL, semantic segmentation	Landscape-scale ecological context supports habitat suitability analysis	Ecosystem-specific tuning required	[20, 21]
Deforestation and degradation prediction	Satellite time series, climatic, and topographic data	RF, XGBoost, MLP–LSTM hybrids	Captures nonlinear drivers; supports proactive intervention	Limited model transferability across regions	[22, 23, 25]
Semantic segmentation for forest change	Satellite imagery	CNNs, transformer-inspired architectures	Detailed spatial representation of degradation patterns	Primarily retrospective; computationally intensive	[24]
Poaching hotspot detection	Incident records, environmental variables	ML risk models, deep learning	Improved identification of high-risk areas	Dependent on historical data quality	[26, 27]
Patrol planning and optimisation	Patrol data, risk maps	ML-informed optimisation	Improved patrol effectiveness without increased effort	Operational and ethical constraints	[28, 29]
Fire risk prediction	Climatic, vegetation, and topographic data	RF, SVM, neural networks	Effective modelling of nonlinear fire drivers	Outputs require expert interpretation	[30, 31]
IoT-enabled forest monitoring	Sensor networks, microclimatic data	Edge AI, lightweight ML/DL	Near-real-time monitoring; reduced cloud dependence	Energy and maintenance constraints	[32]
Cloud-based forest monitoring platforms	Multi-source remote sensing data	Cloud analytics, ML pipelines	High scalability; long-term monitoring capability	Platform dependence and data governance issues	[33, 34]
Conservation decision-support platforms	Patrol records, biodiversity observations	Integrated analytics platforms	Supports adaptive management and reporting	Limited formal performance evaluation	[35, 37]

While this review primarily adopts a qualitative synthesis approach, several studies report quantitative performance metrics such as classification accuracy, F1-score, RMSE, and R^2 values. For instance, deforestation prediction models using XGBoost have reported R^2 values exceeding 0.90, while CNN-based classification models commonly achieve accuracy levels above 85% depending on dataset characteristics. However, direct comparison across studies remains challenging due to differences in datasets, evaluation protocols, and environmental contexts. Therefore, the quantitative results are interpreted as indicative benchmarks rather than strictly comparable performance measures.

B. Observed Strengths and Weaknesses

Strong capabilities have been exhibited by AI-based methods across domains in processing large, heterogeneous datasets and identifying complex spatial and temporal patterns. Deep learning models consistently outperform traditional approaches for image-based tasks like vegetation segmentation, species classification, and land-use change detection. Predictive models take this further by enabling forward-looking risk assessment and resource allocation.

However, there are a number of persisting limitations: many models are developed and evaluated within distinct geographic or ecological contexts, raising concerns about generalization and transferability. Data imbalance persists across most of the wildlife and enforcement-related studies. The evaluation of modeling tasks often focuses on classification accuracy rather than long-term operational reliability. Furthermore, system-level challenges such as constrained energy in IoT deployments and cloud infrastructure dependence restrict wide-scale adoption.

C. Trends across Studies

Three prominent aspects can be identified in the reviewed literature. First, the trend is shifting from retrospective monitoring towards predictive systems for proactive conservation. Second, the trend is emerging towards the incorporation of AI technology with Internet of Things, edge computing, and cloud technology, pointing towards the shift from conceptual to practical implementation. Third, data sources are gaining importance in studies, pointing towards the understanding that conservation in the forests calls for an interdisciplinary approach.

Recent literature between 2023 and 2025 demonstrates a clear transition from isolated AI applications toward integrated forest monitoring ecosystems. While progress has been achieved in remote sensing analytics, biodiversity monitoring automation, and predictive modeling, several systemic gaps remain evident. From the authors' perspective, cross-regional model generalization, system-level evaluation metrics, and interoperability across sensing and analytical platforms represent key unresolved challenges. Future research should therefore prioritize modular architectures, standardized benchmarking, and human-in-the-loop decision-support systems to enable scalable and trustworthy AI-enabled forest governance.

VI. Challenges and Limitations

A. Data Related Issues

AI technology applied to forests and environmental monitoring generally faces limitations related to data quality, accessibility, and representativeness. Incomplete, noisy, or non-representatively distributed remote sensing and IoT data undermine model generalization, especially as a result of cloud cover, seasonal, and non-systematically sampled data points. The absence of qualified data inhibits automation of labeling tasks, making direct comparisons across different studies difficult due to the absence of general benchmarks, contributing to overfitting issues [1]. The establishment of multimodal data collections emphasizes the importance of a general benchmark to enhance model scalability and transferability within different forest environments [40]. Disparities within past data points and biases within data sampling undermine model generalization and ecological fidelity [41].

B. Deployment Constraints

Application of the AI models from the research perspective to practical use in the forests is impeded by generalization gaps, infrastructure constraints, and computational requirements. Model generalization for specific settings may be suboptimal in the context of forests with varying vegetation or climate in different geographic locations, which is a problem known as "domain shift" in the context of AI in forests [1]. Remote edge operations are limited in terms of energy requirements, connectivity, and the potential for real-time monitoring in the absence of adequate solutions for IoT and energy in forests [42]. Model requirements are further exacerbated by the need for light computing in the harsh environment of the forests with intermittent connectivity and a lack of cloud services in the forests [41].

C. Ethical and Ecological Concerns

The use of AI in forest monitoring has several concerns related to issues of equity and privacy, as well as interpreting ecology. The use of high-resolution remote sensing and drones in observations can pose several threats related to human rights in terms of potential observation of human activity without consent in human settlements bordering and within forests [43]. From an ecological point of view, relying heavily on data that can easily be quantified may lead to simplified ecological monitoring by machines and algorithms without considering long-term ecological process dynamics except for human expert review [1].

VII. Conclusion

In this paper, recent works that integrate artificial intelligence for forest monitoring and protection have been discussed in depth. The existing literature regards various applications such as detection by remote sensing, animal monitoring for biodiversity assessment, and predictive models for deforestation, poaching, and forest fires. In general, each application uses artificial intelligence for data processing when it comes to huge amounts of data and automating monitoring that cannot be done by actual surveying.

This review identifies several critical research gaps that must be addressed to advance AI-enabled forest monitoring systems. First, the lack of standardized evaluation frameworks limits the comparability and reproducibility of reported models. Second, most studies rely on region-specific datasets, restricting model generalization across diverse ecological conditions. Third, limited attention has been given to real-world deployment challenges, including sensor reliability, energy constraints, and communication infrastructure. Finally, integrated system-level validation across sensing, analytics, and decision-support layers remains insufficiently explored.

Key takeaways from this review are as follows: (i) AI has demonstrated strong potential in automating large-scale ecological monitoring, (ii) integration with IoT, edge, and cloud technologies is driving a transition toward operational systems, and (iii) future progress depends less on isolated algorithmic improvements and more on robust, interoperable, and field-validated system design.

Overall, AI should be viewed as an enabling tool that complements domain expertise in forest management. Future research must emphasize real-world validation, cross-domain data integration, and collaborative frameworks involving ecologists, technologists, and policymakers to ensure scalable and responsible deployment.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Maddhigalla Lakshumaiah conducted the literature survey, organized and synthesized the reviewed studies, and prepared the initial draft of the manuscript. D. S. Rao conceptualized the review scope, provided critical guidance on structure and content, contributed to technical interpretation and scholarly refinement, and supervised the overall work. Both authors reviewed, revised, and approved the final version of the manuscript.

References

[1] J. Amoah-Nuamah, B. Child, E. Y. Okyere, O. Adams, and J. A. Danquah, "Applications of artificial intelligence in forest health surveillance and management," *Discov. For.*, vol. 1, no. 1, p. 56, Dec. 2025. doi: 10.1007/S44415-025-00061-W

[2] T. Mahmood, M. Asif, and Z. H. Raza, "Revolutionizing forestry with AI GPS and space technologies for sustainable management," *Eur. J. Sci. Innov. Technol.*, vol. 5, no. 1, pp. 275–282, 2025.

[3] M. Kulicki, C. Cabo, T. Trzciński, J. Będkowski, and K. Stereńczak, "Artificial intelligence and terrestrial point clouds for forest monitoring," *Curr. For. Reports*, vol. 11, no. 1, Dec. 2024. doi: 10.1007/S40725-024-00234-4

[4] M. Tholkapiyan, "Examining the impacts of climate variability on agricultural phenology: A comprehensive approach integrating geoinformatics, satellite agrometeorology, and artificial intelligence," *Int. J. Intell. Syst. Appl. Eng.*, vol. 11, no. 6s, pp. 592–598, May 2023.

[5] Z. Xu, D. Jiang, Z. Xu, and D. Jiang, "AI-powered plant science: Transforming forestry monitoring, disease prediction, and climate adaptation," *Plants*, vol. 14, no. 11, May 2025. doi: 10.3390/PLANTS14111626

[6] G. G. Wang, D. Lu, T. Gao *et al.*, "Climate-smart forestry: An AI-enabled sustainable forest management solution for climate change adaptation and mitigation," *J. For. Res.*, vol. 36, no. 1, Nov. 2024. doi: 10.1007/S11676-024-01802-X

[7] Z. Gu and M. Zeng, "The use of artificial intelligence and satellite remote sensing in land cover change detection: Review and perspectives," *Sustainability*, vol. 16, no. 1, Dec. 2023. doi: 10.3390/SU16010274

[8] N. Kale, S. N. Gunjal, M. Bhalerao, H. E. Khodke *et al.*, "Crop yield estimation using deep learning and satellite imagery," *Int. J. Intell. Syst. Appl. Eng.*, vol. 11, no. 10s, pp. 464–471, Aug. 2023.

[9] F. F. Şimşek, "Determination of land use and land cover change using multi-temporal PlanetScope images and deep learning CNN model," *Paddy Water Environ.*, vol. 23, no. 3, pp. 405–423, May 2025. doi: 10.1007/S10333-025-01024-9

[10] N. Camarretta, P. A. Harrison, T. Bailey *et al.*, "Monitoring forest structure to guide adaptive management of forest restoration: A review of remote sensing approaches," *New For.*, vol. 51, no. 4, pp. 573–596, 2020. doi: 10.1007/s11056-019-09754-5

[11] A. U. Rahman, E. Heinaro, M. Ahishali, and S. Junttila, "Dual-task learning for dead tree detection and segmentation with hybrid self-attention U-Nets in aerial imagery," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 144, Nov. 2025. doi: 10.1016/J.JAG.2025.104851

[12] T. Marques, S. Carreira, R. Miragaia, J. Ramos, and A. Pereira, "Applying deep learning to real-time UAV-based forest monitoring: Leveraging multi-sensor imagery for improved results," *Expert Syst. Appl.*, vol. 245, 123107, Jul. 2024. doi: 10.1016/J.ESWA.2023.123107

[13] S. Illarionova, P. Tregubova, I. Shukhratov, D. Shadrin, A. Kedrov, and E. Burnaev, "Remote sensing data fusion approach for estimating forest degradation: A case study of boreal forests damaged by Polygraphus proximus," *Front. Environ. Sci.*, vol. 12, art. no. 1412870, Jul. 2024. doi: 10.3389/FENVS.2024.1412870

[14] L. Jeantet and E. Dufourq, "Improving deep learning acoustic classifiers with contextual information for wildlife monitoring," *Ecol. Inform.*, vol. 77, 102256, Nov. 2023. doi: 10.1016/J.ECOINF.2023.102256

[15] S. Sharma, K. Sato, and B. P. Gautam, "A methodological literature review of acoustic wildlife monitoring using artificial intelligence tools and techniques," *Sustain.*, vol. 15, no. 9, May 2023. doi: 10.3390/SU15097128/S1

[16] M. Bandara, R. Jayasundara, I. Ariyarathne, D. Meedeniya, and C. Perera, "Forest sound classification dataset: FSC22," *Sensors*, vol. 23, no. 4, Feb. 2023. doi: 10.3390/S23042032

[17] I. Mporas, I. Perikos, V. Kelefouras *et al.*, "Illegal logging detection based on acoustic surveillance of forest," *Appl. Sci.*, vol. 10, no. 20, pp. 1–12, Oct. 2020. doi: 10.3390/APP10207379

[18] M. Mulero-Pázmány, S. Hurtado, C. Barba-González *et al.*, "Addressing significant challenges for animal detection in camera trap images: a novel deep learning-based approach," *Sci. Rep.*, vol. 15, no. 1, 16191, May 2025.

[19] H. X. Li, M. Zhang, D. Meng *et al.*, "An automatic identification method of common species based on ensemble learning," *Ecol. Inform.*, vol. 86, 103046, May 2025. doi: 10.1016/J.ECOINF.2025.103046

[20] M. B. Oliveira, H. S. Bernardino, A. B. Vieira, and D. A. Augusto, "Classification of animal species via deep neural networks and species distribution modeling: A systematic review," *Artif. Intell. Rev.*, vol. 58, no. 8, May 2025. doi: 10.1007/S10462-024-11074-W

[21] P. Fergus, C. Chalmers, N. Matthews *et al.*, "Towards context-rich automated biodiversity assessments: Deriving AI-powered insights from camera trap data," *Sensors*, vol. 24, no. 24, Dec. 2024. doi: 10.3390/S24248122

[22] M. Zerrouk, K. A. E. Kadi, I. Sebari, and S. Fellahi, "Machine and deep learning for wetland mapping and bird-habitat monitoring: A systematic review of remote-sensing applications (2015–April 2025)," *Remote Sens.*, vol. 17, no. 21, Oct. 2025. doi: 10.3390/RS17213605

[23] L. Wang, H. Tan, P. Luo, L. Meng, and T. Fei, "Species habitat modeling based on image semantic segmentation," *Sci. Rep.*, vol. 15, 33936, Sep. 2025. doi: 10.1038/s41598-025-09035-6
[24] M. H. Abdullah and Y. T. Mustafa, "Machine learning and SHAP-based analysis of deforestation and forest degradation dynamics along the Iraq–Turkey border," *Earth*, vol. 6, no. 2, Jun. 2025. doi: 10.3390/EARTH6020049
[25] D. Dominguez, L. D. J. del Villar, O. Pantoja *et al.*, "Forecasting Amazon Rain-Forest deforestation using a hybrid machine learning model," *Sustainability*, vol. 14, no. 2, Jan. 2022. doi: 10.3390/SU1402069
[26] I. Md Jelas, M. A. Zulkifley, M. Abdullah, and M. Spraggon, "Deforestation detection using deep learning-based semantic segmentation techniques: A systematic review," *Front. For. Glob. Chang.*, vol. 7, 1300060, Feb. 2024. doi: 10.3389/FFGC.2024.1300060
[27] R. Farzanmanesh, K. Khoshelham, L. Volkova *et al.*, "Using a long short-term memory neural network model to forecast mangrove change in two blue forests conservation projects," *Discov. For.*, vol. 1, no. 1, Jun. 2025. doi: 10.1007/S44415-025-00009-0
[28] L. Kong, H. Wang, C. A. Emogor, V. Börsch-Supan, L. Xu, and M. Tambe. (Aug. 2025). Generative AI against poaching: latent composite flow matching for wildlife conservation. [Online]. Available: https://arxiv.org/pdf/2508.14342
[29] N. Hamed, O. Rana, P. Orozco-terWengel, B. Goossens, and C. Perera, "PoachNet: Predicting poaching using an ontology-based knowledge graph," *Sensors*, vol. 24, no. 24, Dec. 2024. doi: 10.3390/S24248142
[30] L. Xu, S. Gholami, S. McCarthy *et al.*, "Stay ahead of poachers: Illegal wildlife poaching prediction and patrol planning under uncertainty with field test evaluations (short version)," in *Proc. International Conference on Data Engineering*, Apr. 2020, pp. 1898–1901.
[31] Y. Wu, Y. E. Xu, X. Zhang, D. Liu, S. Zhu, and F. Fang, "Improving community-participated patrol for anti-poaching," in *Proc. AAAI Conf. Artif. Intell.*, 2025, vol. 39, no. 27, pp. 28494–28501.
[32] M. Naderpour, H. M. Rizeei, and F. Ramezani, "Forest fire risk prediction: A spatial deep neural network-based framework," *Remote Sens.*, vol. 13, no. 13, Jun. 2021. doi: 10.3390/RS13132513
[33] S. Sharma, P. Khanal, S. Sharma, and P. Khanal, "Forest fire prediction: A spatial machine learning and neural network approach," *Fire*, vol. 7, no. 6, 2024. doi: 10.3390/FIRE7060205
[34] I. D. Arion, I. M. Morar, A. M. Truta *et al.*, "Internet of things (IoT)-based applications in smart forestry: A conceptual and technological analysis," *For.*, vol. 17, no. 1, 44, Dec. 2025. doi: 10.3390/F17010044
[35] B. Halder, J. Bandyopadhyay, and R. Khatun, "Google Earth Engine and Sentinel 1/2 data-based forest degradation monitoring of Sundarban Biosphere Reserve," *Sustain. Horizons*, vol. 9, 100088, Mar. 2024. doi: 10.1016/J.HORIZ.2023.100088.
[36] J. M. Kunberger, M. R. Colón, and A. M. Long, "Using Google Earth Engine to develop interactive mapping tools for conservation planning," *J. Nat. Conserv.*, vol. 87, 126997, Sep. 2025. doi: 10.1016/J.JNC.2025.126997
[37] P. J. Stephenson, "The Holy Grail of biodiversity conservation management: Monitoring impact in projects and project portfolios," *Perspect. Ecol. Conserv.*, vol. 17, no. 4, pp. 182–192, Oct. 2019. doi: 10.1016/J.PECON.2019.11.003
[38] How we use SMART. SMART. [Online]. Available: https://smartconservationtools.org/en-us/SMART-in-Practice/How-we-use-SMART
[39] Ardiantiono, N. J. Deere, D. J. I. Seaman *et al.*, "Improved cost-effectiveness of species monitoring programs through data integration," *Curr. Biol.*, vol. 35, no. 2, Jan. 2025. doi: 10.1016/J.CUB.2024.11.051
[40] N. I. Bountos, A. Ouaknine, I. Papoutsis, and D. Rolnick, "FoMo: multi-modal, multi-scale and multi-task remote sensing foundation models for forest monitoring," *Proc. AAAI Conf. Artif. Intell.*, vol. 39, no. 27, pp. 27858–27868, Apr. 2025. doi: 10.1609/AAAI.V39I27.35002
[41] G. Ali, M. M. Mijwil, I. Adamopoulos, and J. Ayad, "Leveraging the internet of things, remote sensing, and artificial intelligence for sustainable forest management," *Babylonian J. Internet Things*, vol. 2025, pp. 1–65, Jan. 2025. doi: 10.58496/BJIOT/2025/001
[42] A. Aral, "The promise of neuromorphic edge AI for rural environmental monitoring," *Environ. Data Sci.*, vol. 3, e34, Jan. 2024. doi: 10.1017/EDS.2024.36
[43] AI for Forestry: Protecting Our Forests with Cutting-Edge Technology. Accel.AI. [Online]. Available: https://www.accel.ai/anthology/2024/12/1/q05adnyv5iwgvd08kvlogagtk4qheq

Maddhigalla Lakshumaiah received his B.Tech. degree from Sri Venkateswara University (SVU), Tirupati, India, in 2005, and the M.Tech. degree from Jawaharlal Nehru Technological University (JNTUA), Anantapur, India, in 2011. He has 15 years of teaching experience in engineering education. He is currently working as an Assistant Professor at KL University, India. His academic interests include teaching, curriculum development, and mentoring undergraduate and postgraduate students. He has been actively involved in academic activities and contributes to quality technical education.

Dr. D. S. Rao received his Ph.D. degree from the National Institute of Technology (NIT), Rourkela, and is currently a Professor in the Department of Computer Science and Engineering at the KLEF (KL Deemed to be University), Hyderabad Campus. He is an associate member of the Institute of Noise Control Engineering (INCE), USA. He has published more than 20 peer-reviewed research articles indexed in SCI and Scopus databases, along with 7 patents and 7 book chapters. His research contributions span soft computing, noise prediction, noise-induced hearing loss, and lung cancer prediction. He also serves as a reviewer for three SCI-indexed journals and is a member of the editorial boards of two academic journals. In recognition of his contributions, Dr. Rao has received several awards from various organizations, including those in the field of noise pollution and healthcare.