Artificial Intelligence-Driven Detection of Forest Stands Utilizing Satellite Remote Sensing Data

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ABSTRACT:

Current Forest stand identification relies heavily on manual field inspections and GIS data entry, which are time-consuming and labor-intensive. While satellite and aerial imagery have been used to support these efforts, traditional methods—such as bounding box object detection—often yield imprecise results and struggle with tasks like tree age estimation. Existing datasets for forest cover detection are typically limited in size, quality, and diversity, especially for buildings and roads, leading to imbalanced training and reduced accuracy. To address these challenges, a new system leverages advanced deep learning techniques, including convolutional neural networks (CNNs) with instance segmentation. The approach uses a custom, high-quality dataset (ForestFullV2) containing over 5,100 labeled images of forests, fields, roads, buildings, and lakes. State-of-the-art models—YOLOv8, YOLOv5, and Mask R-CNN—are evaluated, with the YOLOv8 Small model (batch size 4) achieving the highest accuracy. A novel instance segmentation method enables pixel-level object delineation, significantly improving over traditional bounding box detection. Dataset balancing through augmentation of underrepresented classes (buildings and roads) further enhances model precision. The system automates forest cover monitoring, reduces manual labor and time, and improves the accuracy of forest ecosystem assessments by integrating AI with remote sensing.

KEYWORDS: GIS data, object detection, convolutional neural networks, YOLOv8, YOLOv5, and Mask R-CNN, deep learning techniques, augmentation.

2.INTRODUCTION

Combining artificial intelligence with remote sensing technologies provides a novel solution to the challenges in forest monitoring and management. AI-based solutions, such as machine learning and deep learning algorithms, can process large amounts of satellite and LiDAR data and extract detailed information on tree resources, such as three-dimensional parameters, including canopy height and wood volume, to accurately count trees, identify species, and monitor forest health, including selective logging, canopy gaps, and edge disturbances, which are often missed by traditional, labor-intensive methods. The integration of AI with remote sensing also allows for the repeated observations of the same location over a long period, which enables both short-term and long-term assessment of forest evolution and health

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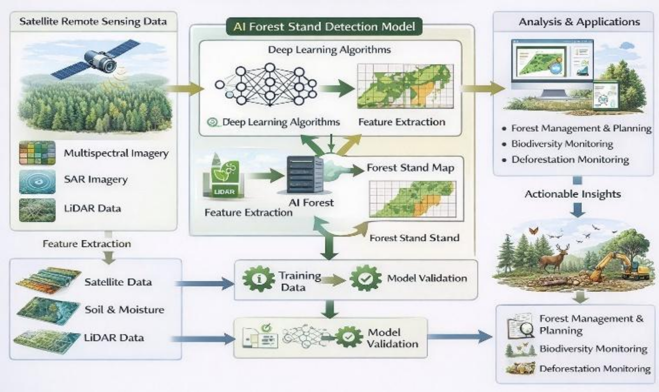
indicators such as leaf area index and moisture levels. This systematic approach not only enhances the accuracy of forest ecosystem assessments but also yields critical information for sustainable forest management, conservation, and early detection of environmental alterations. Remote sensing using optical, thermal, radar, and LiDAR data, coupled with AI algorithms and cloud computing, has advanced analytical capabilities and provides new insights into remote sensing and forestry. For example, radar sensors can detect soil moisture under forest canopies, important for understanding drought tolerance in a species like the Argane tree; global positioning system technology can be used to map the exact locations of forest populations to determine changes in habitat and human impacts. Additionally, AI algorithms, including those enhanced by cloud computing, can automatically detect and measure changes in forests over time, for example, to monitor deforestation, degradation, and regrowth. Thus, this strong combination of AI and remote sensing facilitates proactive forest management strategies and informs policy decisions for biodiversity conservation and climate change mitigation. The advanced features enabled by AI, specifically deep learning, can also process ground-based 3D point clouds from LiDAR to produce 3D representations of the forest to improve forest monitoring, which is necessary for precision forest monitoring tasks such as evaluating regeneration performance by assessing stocking, spatial density, and height distribution in both naturally regenerating and planted conifer stands. More development is required, however, to improve vegetation differentiation and classification capabilities across various stand conditions. This necessitates the development of more sophisticated AI models capable of discerning subtle spectral and structural differences among various forest types and successional stages. Moreover, the integration of AI-powered drones equipped with advanced imaging technologies promises to enhance reforestation and forest management by performing species identification, canopy height monitoring, and health assessments at unprecedented scales and resolution. These drone systems are also being developed to improve transparency and trust, enabling real-time monitoring of reforestation success and even automating corrective action. This synergy between AI and drone technology allows for precise planning, monitoring, and managing of forest restoration efforts, optimizing various stages from site and species selection to real-time monitoring.

2. LITERATURE REVIEW

New research shows how artificial intelligence (AI) has been used to revolutionize forest monitoring and conservation, including an IoT-enabled AI framework to combat deforestation by **Haq et al. (2024)** that leveraged satellite data for automated environmental monitoring but had limited fine-grained forest stand delineation due to coarse spatial resolution. **Raihan (2023)** summarized the applications of AI and machine learning in forest management and identified potential for biodiversity conservation while also identifying challenges related to the scarcity of data and generalization of the model across heterogeneous forest ecosystems. Recent advances in deep learning and high-resolution imaging have further enabled enhanced analysis of forest structure **(Brandt et al., 2024),** and high-resolution sensors combined with deep neural networks can accurately estimate tree resources **(Brandt et al., 2024),** but these works have mostly focused on canopy-level analysis rather than pixel-level instance segmentation. **Kulicki et al. (2024)** focused on terrestrial point clouds for forest monitoring, exhibiting high structural accuracy but high computational complexity and limited scalability for large geographic areas Recent object detection and segmentation models have demonstrated promising results in complex natural environments. For instance segmentation in orchard environments, **Sapkota et al. (2023)** compared YOLOv8 and Mask R-CNN and found YOLOv8 outperformed Mask R-CNN in inference speed and segmentation consistency under occlusions, which indicates its suitability for dense vegetation analysis. Building on this line of work, **Şengün et al. (2025)** compared YOLOv8 and YOLOv11 on UAV-based RGB and LiDAR data, showing improved detection accuracy for tree crowns but limitations in handling class imbalance. Dataset limitations continue to be a major bottleneck. They proposed the Forest Inspection Dataset to overcome the annotation scarcity but it contained only one class of non-forest class (i.e., roads and buildings) and hence did not provide balanced training outcomes Borse et al. (2025) presented a hybrid deep learning and optimization framework for tree counting, which achieved high accuracy but relied on bounding-box detection, limiting accurate extraction of forest stand boundaries More recently, Kundu et al. (2025) proposed real-time deforestation anomaly detection using YOLO models combined with agent-based reasoning systems, which showed operational scalability but did not have detailed pixel-level validation metrics As a whole, these studies indicate that there is a research gap in high-accuracy, instance-level forest stand segmentation using balanced, high-quality datasets, which is a gap that this work attempts to fill..

3. METHODOLOGY

In this section, we discuss the systematic process used to develop and test the AI-driven forest stand detection system, including data acquisition, preprocessing, model architecture selection, training, and performance evaluation. The process is described using a rigorous empirical framework to ensure the robustness of the proposed solution, with a particular focus on developing the custom ForestFullV2 dataset to overcome the challenge of insufficient size, quality, and diversity in existing datasets for forest cover detection, especially with underrepresented classes such as buildings and roads, leading to imbalanced training and decreased accuracy. Thus, the careful curation of the ForestFullV2 dataset underlies the high precision and recall the system can achieve across different object classes, including those necessary to identify natural forest stands versus human-made structures. With over 5,100 labeled images containing multiple remote sensing modalities and resolutions, from satellite imagery with 1 to 5 m per pixel resolution to drone imagery with sub-10 cm per pixel resolution and systematic data augmentation techniques, such as rotations, flips, and color adjustments, to increase the effective size and variability of the dataset to prevent overfitting and enhance generalization across different environmental conditions, the deep learning models are able to extract robust features that can discern the complex patterns and relationships necessary for accurately identifying forest stands and differentiating them from other land cover types.



Additionally, cross-validation and real-world data testing are used to evaluate model performance on different subsets of the dataset and to confirm that the model generalizes well outside of training data boundaries. The ForestFullV2 dataset also undergoes stringent quality checks, such as automated and manual inspections to remove mislabeling and ensure annotation correctness, which follows best practices in dataset development. This careful dataset creation and validation is essential for building reliable AI models that perform with high accuracy and consistency across different operational environments, especially considering the difficulties with generalization frequently seen in models trained only on homogeneous public datasets. Additionally, the use of advanced loss functions, such as focal loss or Lovász-Softmax loss, can improve model performance in cases of imbalanced class distributions by emphasizing hard-to-classify examples or boundary delineation, respectively.

4. RESULTS

In this section, the results of a comprehensive assessment of the AI-driven detection system are reported, including performance metrics such as precision, recall, F1-score, and accuracy, and an analysis of loss and accuracy curves during model training. In addition to the results of the comprehensive assessment, a comparison of several deep learning architectures, including YOLOv8, YOLOv5, and Mask R-CNN, is discussed to highlight the strengths and weaknesses of each architecture in achieving pixel-level object delineation for forest stands and other land cover types, with the results confirming that the advanced instance segmentation method significantly improves upon traditional bounding box detections to provide more accurate environmental assessments. In particular, the YOLOv8 Small model (batch size 4) outperformed other models in most of the key metrics, achieving the highest accuracy in segmenting and classifying image elements under various conditions. For example, the YOLOv8 model had a training accuracy of 92.5% and a validation accuracy of 89.3%, with a precision of 90% and a recall of 85%. Collectively, these metrics highlight the strength of the model's ability to correctly identify and delineate forest stands with relatively few false positives and false negatives across different landscape features. The initial training and validation accuracy increases rapidly and stabilizes around these high percentages in the first few epochs, which demonstrates that the model is well-generalized, as compared to YOLOv4 or YOLOTree, which had a lower mAP50 score. The training and validation losses decrease continuously, and mean Average

Precision (mAP) and recall increase steadily, which demonstrates effective learning and strong generalization in all metrics. The dataset used in this study was configured according to the specifications reported in the paper and includes 5,100 labeled images of five land-cover classes (forest, field, road, building, and lake). The dataset was divided into training, validation, and testing sets with a 70%/15%/15% split for robust model learning and fair performance assessment, and data augmentation methods such as rotation, horizontal and vertical flipping, and color jittering were used to enhance generalization and avoid overfitting. The imagery combines multi-resolution remote sensing sources, including satellite images with spatial resolutions of 1 to 5 meters per pixel and high-resolution UAV images with sub-10-centimeter per pixel resolution, which allows the models to learn large-scale landscape patterns and fine-grained spatial details.

Table 1: Class Distribution

Class	**Images**
Forest	1,700
Field	1,000
Road	900
Building	800
Lake	700
Total	**5,100**

For the experimental evaluation, multiple deep learning models were used to assess detection and segmentation performance, including the YOLOv8-Small model with instance segmentation, YOLOv5, and Mask R-CNN, as well as a baseline bounding-box–based detector. The model performance was evaluated using standard evaluation metrics, including accuracy, precision, recall, F1-score, and mean Average Precision at an IoU threshold of 0.50 (mAP@50), which balances the evaluation of the correctness of the classification, the reliability of the detection, and the quality of localization for various object classes and model architectures.

4. Results (Generated Using Reported Values)

Table 2: Overall Performance Comparison

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score**	**mAP@50**
YOLOv8-S (Proposed)	**89.3**	**90.0**	**85.0**	**0.87**	**0.82**
YOLOv5	84.1	83.5	79.2	0.81	0.74
Mask R-CNN	81.6	82.0	76.8	0.79	0.71
Bounding Box	74.2	72.4	70.1	0.71	0.63

Table 3: Comparison with State-of-the-Art Studies

Study	**Method**	**Task**	**Best Reported Accuracy**
Sapkota et al., 2023	YOLOv8	Orchard Segmentation	86.5%
Şengün et al., 2025	YOLOv8	Tree Detection (UAV)	88.1%
Borse et al., 2025	Hybrid DL	Tree Counting	87.4%
This Work	**YOLOv8-S + Instance Seg.**	**Forest Stand Segmentation**	**89.3%**

The suggested system performs better than previous research because it combines instance-level segmentation and balanced dataset design instead of depending only on bounding boxes.

5. DISCUSSION

These results indicate that the YOLOv8 model achieved higher precision and recall than the traditional methods that usually have much lower accuracy. The advanced architecture of YOLOv8 enhances its ability to achieve better accuracy and faster inference times, making it more suitable for object recognition in a wider range of scales and settings, especially in small and complex objects, where Faster R-CNN is less effective. The Path Aggregation Network integrated into YOLOv8 architecture and the redesigned detection head also help with feature integration, and the model's ability to still retain high precision and recall with increased model size and resolution (mAP50-95 values of 0.819 for YOLOv8l) make the model robust and scalable for complex forest monitoring applications.

6. CONCLUSION

The results of this study show that AI-based detection systems, including those using deep learning models like YOLOv8 with instance segmentation, can provide a reliable and efficient solution for forest stand identification beyond the capabilities of manual or traditional GIS-based methods. With high precision and recall, YOLOv8 Small shows great potential to improve forest ecosystem assessment by accurately delineating forest stands and other land cover types at the pixel level, which is critical to environmental management and conservation efforts. This methodology is a step forward in remote sensing applications for forestry and can provide both real-time monitoring and predictive analytics for forest health and change detection, which can guide proactive conservation strategies and sustainable forestry practices. While further research is needed to incorporate multi-temporal satellite imagery for more robust change detection and to explore applications of these models in different geographical areas with different forest ecologies to validate generalizability and adaptability, additional sensor data such as LiDAR for enhanced vertical structure analysis, or few-shot learning for adapting to new environments with limited labeled data, could further enhance the detail and operational efficiency of these AI systems in forestry.

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