

Smart Urban Greenery: Predictive Analytics and Human-in-the-Loop Feedback for Tree Management

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Abstract

Urban greenery is essential for sustainable cities, contributing to climate regulation, biodiversity preservation, and human well-being. However, traditional tree maintenance strategies often rely on subjective assessments and fixed schedules, leading to inefficiencies in resource allocation and delayed interventions. This study presents AI-TreeCare, an intelligent urban tree maintenance system developed for Putrajaya that integrates machine learning, real-time monitoring, and human-in-the-loop feedback to optimize pruning, watering, pest management, and overall tree health. Literature on predictive modeling, ensemble learning, and human-assisted decision-making underscores the potential of AI to enhance ecological management and support Sustainable Development Goals (SDG 6, 11, and 15). A mixed-method research design was employed. Quantitative data, including tree inventories, environmental metrics, and images, were analyzed using logistic and linear regression, Random Forest, and YOLO-based image detection models. Staff feedback was incorporated via sentiment analysis to refine AI recommendations. Model performance was evaluated using accuracy, R^2 , precision, recall, and mean average precision (mAP). Results demonstrated high predictive performance: pruning accuracy of 99.5%, water requirement accuracy of 100%, pest severity R^2 of 0.98, and overall health scoring R^2 of 0.99. Image-based detection achieved 97% accuracy and 0.94 mAP. Staff feedback aligned with AI recommendations 92% of the time, confirming reliability and practical usability. The study concludes that AI-TreeCare effectively automates tree care decisions, optimizes resources, and integrates human expertise, supporting sustainable urban forestry management and contributing to SDGs. Recommendations include scaling the system, integrating IoT sensors, and continuous model retraining to enhance real-time responsiveness and sustainability outcomes..

Keywords: Urban forestry, Artificial intelligence, Human-in-the-loop, Tree maintenance, Smart cities

INTRODUCTION

Urban green infrastructure, particularly trees, plays a critical role in enhancing environmental quality, supporting biodiversity, mitigating urban heat island effects, and improving human well-being (Nowak et al., 2014; Livesley et al., 2016). In rapidly urbanizing environments, the sustainable management of urban trees is increasingly complex due to constraints in labor, budget, environmental stressors, and the sheer scale of tree populations (Jim & Chen, 2008). Traditional tree maintenance strategies have typically relied on fixed schedules and subjective assessments conducted by personnel in the field. While these practices offer some degree of structure, they are limited in their capacity to adapt to real-time conditions, incorporate heterogeneous data sources, and anticipate problems before they escalate (Konijnendijk et al., 2018). Urban forestry is thus confronted with gaps in predictive capacity, resource optimization, and integration of human expertise with systematic data analysis.

The adoption of intelligent systems in environmental management has shown potential to address these gaps. Artificial intelligence (AI) and machine learning techniques have been applied in diverse domains such as precision agriculture, ecological monitoring, and smart city infrastructures to enhance prediction, automate decision-making, and streamline labor-intensive tasks (Liakos et al., 2018; Kamilaris & Prenafeta-Boldú, 2018). However, the application of AI specifically for urban tree maintenance remains nascent. The complexity of tree

care decisions such as determining optimal pruning periods, estimating water requirements, and identifying early signs of pest infestations requires systems capable of learning from multi-modal data, including biological metrics, environmental indicators, and human feedback. Existing tree inventory systems tend to be static databases, lacking interactive analytical capacity or real-time responsiveness (McPherson et al., 2016). This limitation contributes to inefficiencies in maintenance scheduling, suboptimal allocation of resources, and increased vulnerability of urban trees to health decline.

A major challenge arises from the disparity between the dynamic nature of urban ecosystems and the static methods traditionally employed in urban forestry. Urban trees experience rapid changes in conditions due to weather events, human activities, and biological pressures that static rule-based systems cannot effectively capture (Anderson & Cordell, 1988). Furthermore, maintenance decisions often depend on subjective assessments that vary across individual inspectors, leading to inconsistencies in care quality and outcomes. While urban forestry staff possess valuable experiential insights, there is limited infrastructure to systematically integrate their feedback into robust decision support systems. Consequently, urban forestry management faces a dual problem: the absence of adaptive analytical tools that can interpret large, diverse datasets and the lack of structured pathways to incorporate expert human judgment into automated systems.

These challenges suggest a pressing need for an intelligent system that can unify machine learning, real-time monitoring, and practitioner feedback to optimize tree maintenance. Such a system would not only improve predictive accuracy for maintenance needs, but also support sustainable resource use and proactive care interventions.

The purpose of this study is to develop and evaluate *AI-TreeCare*, an integrated AI-driven urban tree maintenance system that automates care recommendations, optimizes resource allocation, incorporates staff feedback, and enables real-time health monitoring to enhance urban forestry outcomes in Putrajaya.

Literature Review

Prior research on urban tree management has examined individual components of decision systems such as predictive modeling for plant health, resource optimization, and human-computer interaction, yet rarely in an integrated AI framework. Studies investigating tree health diagnostics have highlighted the potential of machine learning (ML) to detect stress and disease from multispectral imagery and field data. For instance, deep learning models have been applied to classify plant diseases with high accuracy using visual data, demonstrating convolutional neural networks' efficacy in automating health assessment tasks traditionally performed by experts (Barbedo, 2018). Similarly, object detection architectures such as YOLO (You Only Look Once) have been utilized to recognize types of foliar damage and pest signs, facilitating rapid and scalable surveillance (Redmon & Farhadi, 2018). These studies provide a precedent for integrating automated image-based health detection into urban forestry systems.

In the domain of predictive modeling for maintenance needs, regression-based approaches have been widely studied. Linear and logistic regression models have been used to determine irrigation scheduling and pruning requirements based on environmental variables and phenological indicators (Jones et al., 2019). Regression models' interpretability makes them valuable for understanding relationships between predictors (e.g., soil moisture, rainfall) and outcomes (e.g., water requirement levels). Ensemble methods such as Random Forest have shown enhanced performance in complex ecological datasets by capturing nonlinear interactions among predictors, especially in estimating tree health indices and environmental stress responses (Prasad et al., 2006). The combination of regression and ensemble learning in the *AI-TreeCare* system is grounded in the evidence that diversified model techniques can improve prediction reliability across maintenance tasks.

Human feedback integration, another critical variable in *AI-TreeCare*, draws on research from human-in-the-loop (HITL) learning paradigms. HITL frameworks leverage practitioners' domain knowledge to correct and refine algorithmic predictions, thereby enhancing both model performance and user trust (Amershi et al., 2014). In agricultural decision systems, sentiment analysis tools such as VADER have been used to interpret qualitative staff feedback and translate it into quantitative adjustments, demonstrating that sentiment-based interpretation can enrich model outputs beyond operational metrics (Hutto & Gilbert, 2014). These findings justify the inclusion of staff feedback logs as a meaningful data source in adaptive tree care recommendations.

Urban environmental management literature has established theoretical foundations for integrating technology with ecological stewardship. The socio-ecological systems (SES) framework posits that sustainable environmental management arises from dynamic interactions between social actors and ecological processes (Ostrom, 2009). AI-TreeCare operationalizes this by linking data-driven models with human decision-making, reflecting a system where technological intelligence and practitioner experience co-evolve. Additionally, theories of smart cities emphasize the use of real-time analytics, sensor networks, and predictive systems to optimize urban infrastructure, including green assets (Batty et al., 2012). This conceptual underpinning situates AI-TreeCare within a broader discourse on intelligent urban environments.

The conceptual framework for this study positions AI-TreeCare as an integrative architecture where heterogeneous data streams environmental metrics, imagery, and human feedback—are processed through machine learning models to generate actionable maintenance recommendations. The framework aligns with the principle that effective urban forestry management depends on predictive insight, adaptive learning, and real-time system responsiveness (McHugh et al., 2020). By synthesizing prior studies across relevant domains, the design of AI-TreeCare is theoretically anchored in ML efficacy, human-centered feedback integration, and socio-ecological systems thinking.

Research Methodology

This study employed a mixed-method research design combining quantitative and qualitative procedures to rigorously examine the development and evaluation of *AI-TreeCare*, an AI-driven urban tree maintenance system. A mixed-method approach allows for a comprehensive understanding of both numerical model performance and user experience, aligning with recent recommendations for environmental and AI-based research (Ren, 2023). The research design encompasses systematic data collection, targeted sampling, model development and evaluation, and robust analytical procedures to ensure that findings are valid, reliable, and applicable to urban forestry management contexts (Kharuddin & Ismail, 2017).

The research design followed a sequential explanatory strategy in which quantitative AI model development and performance measurement were conducted first, followed by qualitative interpretation of system usability and staff feedback. Quantitative components focused on algorithm training, predictive evaluation, and statistical validation, whereas qualitative analysis captured practitioners' insights through structured feedback logs and thematic interpretation of commentary. Such mixed designs are increasingly recognized as best practice for socio-technical system evaluations, especially where human and machine judgments must be integrated (Bayhan et al., 2025).

Sampling and Data Collection Procedures were designed to balance representativeness with practicality. *AI-TreeCare* utilized multiple data sources: (1) existing tree inventories containing attributes such as species, age, and geolocation; (2) localized environmental datasets including weather and soil moisture metrics; (3) image datasets capturing tree conditions; and (4) structured feedback logs from maintenance staff. Tree inventory and environmental data were drawn from municipal forestry records and environmental agencies to ensure real-world relevance and comprehensiveness. For imagery, a purposive sampling strategy was adopted, selecting trees exhibiting a range of visible health conditions to enhance model robustness across phenotypes. Purposive sampling is appropriate when the aim is to include a wide variation of conditions within a manageable dataset (Sekaran & Bougie, 2016). Staff participants were selected through criterion sampling, in which personnel with at least one year of maintenance experience were invited to contribute feedback, ensuring that input came from domain-relevant professionals (Kharuddin et al., 2018).

Data collection for the quantitative phase involved automated extraction of tree and environmental records, preprocessing of imagery using standard computer vision techniques, and annotation of health indicators. Feedback logs were gathered via a standardized form that prompted staff to evaluate AI recommendations and report decision outcomes. To preserve data quality, preprocessing steps such as missing-value handling, normalization, and feature encoding were performed prior to analysis, following established data science practices (Zhu, 2023).

Data Analysis integrated statistical and machine learning methods to model maintenance needs and evaluate system performance. Regression models logistic regression for classification tasks (e.g., pruning vs no pruning)

and linear regression for continuous estimation (e.g., watering volume) were first developed to establish baseline predictive performance. Ensemble techniques such as Random Forest were used to generate composite health scoring due to their capacity to model nonlinear interactions and reduce overfitting (Muñoz-Alegría et al., 2025). Performance metrics included accuracy, precision, recall, and R^2 scores for regression tasks, computed using standard formulae such as:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

where y_i are observed values, $\hat{y}_i$ are predicted values, and $\bar{y}$ is the mean of observed values. Image-based detection models such as YOLO were evaluated using intersection over union (IoU) and mean average precision (mAP) metrics to quantify localization and classification performance in tree health imagery.

Qualitative analysis of staff feedback was conducted using thematic content analysis to extract patterns in sentiment and recommendation alignment. Sentiment analysis tools like VADER were used to quantify qualitative input into numerical sentiment scores, enabling integration with model evaluation. This blended analytical strategy ensured that AI performance was assessed in tandem with human assessments, supporting actionable insight and iterative system refinement.

Overall, this methodology ensured that findings reflect both machine analytic capability and practical usability, establishing a holistic evaluation framework for AI-assisted urban tree maintenance.

Data Analysis, Results, and Findings

The collected data were analyzed to evaluate the performance of *AI-TreeCare* in predicting urban tree maintenance needs, including pruning requirements, water allocation, pest severity, and overall health scoring. Quantitative analyses were performed using regression, ensemble, and image-based models. Logistic regression was used for categorical tasks such as pruning decisions, while linear regression estimated continuous variables, including water volume requirements. Random Forest was employed to calculate composite tree health scores, capturing nonlinear relationships among environmental, biological, and feedback features. Image-based analysis utilized the YOLO algorithm for early detection of visible pest or disease symptoms. Model performance was evaluated using standard statistical metrics such as accuracy, R^2 , precision, recall, and mean average precision (mAP) for image detection tasks (Muñoz-Alegría et al., 2025; Ren, 2023). Additionally, qualitative staff feedback was analyzed using sentiment scoring through VADER to assess alignment between AI recommendations and practitioner assessments (Hutto & Gilbert, 2014).

The analysis framework integrated machine learning predictions with staff feedback to evaluate both predictive reliability and practical usability. The aim was to determine how well *AI-TreeCare* could provide actionable recommendations that align with expert judgment while optimizing operational efficiency. The predictive performance of *AI-TreeCare* across the four main variables is summarized in Table 1.

Table 1: Predictive Model Performance for Urban Tree Maintenance Variables

Variable	Model Used	Accuracy / R^2	Precision	Recall	mAP (if applicable)
Pruning Need (Yes/No)	Logistic Regression	99.5%	0.995	0.994	N/A
Water Requirement (L)	Linear Regression	100%	N/A	N/A	N/A
Pest Severity (1–5)	Linear Regression	0.98	N/A	N/A	N/A

Variable	Model Used	Accuracy / R ²	Precision	Recall	mAP (if applicable)
Overall Health Score (0–100)	Random Forest	0.99	N/A	N/A	N/A
Image-based Damage Detection	YOLOv5	97%	0.96	0.95	0.94

The system demonstrated exceptionally high predictive accuracy for pruning needs (99.5%) and water allocation (100%). Pest severity predictions and overall health scoring showed strong model fit, with R² values of 0.98 and 0.99, respectively, indicating that the models reliably captured variation in tree health outcomes based on environmental and biological features. YOLO-based image detection achieved a mean average precision of 0.94, confirming robust identification of visual symptoms such as leaf damage and pest infestation.

The results indicate that AI-TreeCare is highly effective in predicting maintenance needs for urban trees. The near-perfect accuracy in pruning decisions suggests that the model can reliably determine when interventions are necessary, thereby reducing unnecessary labor and optimizing operational schedules. Accurate water requirement predictions allow for precise irrigation planning, minimizing water waste and ensuring trees receive adequate hydration even under fluctuating environmental conditions. Pest severity predictions with R² of 0.98 demonstrate that the system can quantify potential biological threats, enabling targeted interventions before problems escalate.

The overall health score generated by the Random Forest model closely aligns with environmental indicators and observed tree conditions. This composite scoring system provides an intuitive metric for maintenance teams to prioritize care interventions. High performance of the image-based detection module indicates that visual surveillance can be automated to detect early signs of damage or disease, which supports proactive management strategies.

Integration of staff feedback further strengthened the findings. Sentiment analysis of qualitative input showed that 92% of AI-generated recommendations aligned with expert judgment, demonstrating that the system effectively incorporates human insights into data-driven decision-making. Staff were able to validate and adjust the AI predictions in real time, which enhanced both the system's reliability and user trust.

Additionally, the predictive dashboards offered real-time monitoring of maintenance needs, allowing maintenance teams to schedule pruning, watering, and pest control efficiently. Visual summaries and alert mechanisms facilitated quick identification of trees requiring immediate attention, which is particularly beneficial in large urban environments with thousands of individual trees. The combined quantitative and qualitative results suggest that AI-TreeCare not only enhances predictive accuracy but also supports operational decision-making in a practical, real-world context.

The findings also underscore the potential of AI-assisted urban forestry to improve resource allocation. By accurately predicting maintenance needs, the system allows for more efficient use of labor, water, and chemical treatments for pest management. This contributes to sustainable urban greenery management by reducing operational costs and environmental impact. Furthermore, the integrated approach ensures that predictive algorithms do not operate in isolation but are continuously refined based on human feedback, fostering an adaptive learning system that evolves over time.

In conclusion, the analysis demonstrates that AI-TreeCare effectively combines predictive modeling, image-based detection, and human feedback to optimize urban tree maintenance. The system provides actionable insights, supports proactive interventions, and promotes sustainability in urban forestry management.

Discussion and Recommendations

The findings of this study demonstrate that *AI-TreeCare* successfully addresses the core research objectives: automating tree care decisions, optimizing resource allocation, integrating staff feedback, and enabling real-time monitoring. The system's predictive models achieved high accuracy for pruning needs (99.5%), water requirements (100%), pest severity ($R^2 = 0.98$), and overall health scoring ($R^2 = 0.99$), indicating that *AI-TreeCare* can reliably guide maintenance interventions. These results directly fulfill the objective of automating tree care decisions, illustrating the potential of machine learning models to reduce human error and enhance operational efficiency, consistent with prior research emphasizing the role of predictive modeling in ecological management (Barbedo, 2018; Prasad et al., 2006).

Resource optimization, the second objective, was achieved through precise estimations of water usage and prioritization of maintenance tasks based on health scores. By accurately predicting irrigation requirements and identifying trees most in need of attention, *AI-TreeCare* facilitates sustainable management of urban greenery. This aligns with SDG 6 (Clean Water and Sanitation) by promoting efficient water use, and SDG 11 (Sustainable Cities and Communities) by improving urban environmental planning (UN, 2022). Furthermore, the system reduces waste of manpower and materials, echoing findings in urban forestry literature that emphasize the importance of data-driven resource allocation (Konijnendijk et al., 2018).

The integration of staff feedback underscores the system's human-in-the-loop design, which refines predictions and enhances alignment with expert judgment. Sentiment analysis of qualitative inputs showed a 92% agreement rate between AI recommendations and human assessments, supporting the objective of incorporating practitioner knowledge into automated systems. This finding reinforces the socio-ecological systems perspective, which highlights the value of combining technological intelligence with human expertise for adaptive management (Ostrom, 2009). It also addresses concerns identified in prior studies regarding the limitations of purely algorithmic decision-making in dynamic ecological environments (Amershi et al., 2014).

Real-time monitoring, achieved through predictive dashboards and alert systems, enabled maintenance teams to proactively respond to emerging threats, such as pest infestations or water stress. The image-based detection module (YOLO) demonstrated 97% accuracy and 0.94 mAP, highlighting the system's ability to identify visual symptoms early, thus supporting SDG 15 (Life on Land) by contributing to the preservation of urban biodiversity (Livesley et al., 2016). These findings collectively suggest that *AI-TreeCare* not only meets operational objectives but also advances environmental sustainability and resilience in urban forestry management.

In conclusion, *AI-TreeCare* exemplifies the transformative potential of AI in sustainable urban tree maintenance. The system's high predictive accuracy, integration of staff expertise, and real-time monitoring capabilities confirm that machine learning can complement human judgment to improve efficiency and resource utilization. Literature reviewed in this study supports these findings: predictive modeling enhances maintenance scheduling (Jones et al., 2019), ensemble learning improves health assessments (Prasad et al., 2006), and HITL feedback mechanisms increase model reliability (Amershi et al., 2014).

Recommendations arising from this study include expanding *AI-TreeCare* to incorporate mobile interfaces for field personnel, integrating IoT sensors to collect real-time soil moisture and microclimate data, and implementing periodic retraining of models to incorporate new environmental trends and operational feedback. Additionally, scaling the system to other urban regions and incorporating citizen-reported data could enhance coverage, improve predictive robustness, and foster community engagement in urban greenery management. Future research should also investigate the long-term impact of AI-guided interventions on urban ecosystem health and resource efficiency...

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