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Smart Urban Ecosystems for Biodiversity Conservation Using Artificial Intelligence and Digital Technologies

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Abstract

Biodiversity loss caused by rapid urbanization, fragmentation of habitats, ecological degradation and the lack of efficient monitoring of the environment, as well as the lack of integration of ecological intelligence in real-time decision making for conservation, are still significant challenges. Despite these trends, the implementation of existing smart-city solutions fails to combine ecological intelligence with real-time conservation decision making. The proposed Smart Urban Ecosystem Framework for this study is based on the Internet of Things (IoT) sensors, satellite images, Unmanned Aerial Vehicle (UAV), computer vision, graph neural networks (GNN), explainable artificial intelligence (XAI), and geospatial analytics, which can be used to continuously assess biodiversity and enable adaptive ecosystem management. Within a dynamic digital twin, multi-source environmental data are fused, and habitat quality is monitored, species distribution is predicted, biodiversity hotspots are identified, ecological connectivity is evaluated and conservation interventions are recommended based on interpretable predictive models. The experimental evaluation shows that the species classification accuracy of 97.1% and habitat suitability prediction accuracy of 95.4%, and the precision of detecting biodiversity hotspots and assessing ecological connectivity accuracy 96.2% and 94.3%, respectively, and the accuracy of predicting biodiversity risk of 95.1% are high. Monitoring time was reduced by 43.6% and conservation planning efficiency was increased by 31.8% compared with conventional methods. The proposed framework brings together, in a unified, explainable and real-time digital ecosystem, the world of artificial intelligence and urban ecological management. The research provides a platform towards resolving the challenges of decision support for biodiversity-positive urban planning that is scalable, data-driven, and data-informed, driving towards resilient smart cities by intelligent ecosystem conservation and proactively managing the environment.

Keywords— Smart Urban Ecosystems; Biodiversity Conservation; Artificial Intelligence; Digital Twin; Sustainable Cities and Communities

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I. Introduction

Urbanization is increasingly developing in unprecedented speed, converting natural environment to built environment and causing great stress on biodiversity due to habitat loss and fragmentation, species displacement and ecological degradation. The management of protected areas and urban green spaces becomes increasingly intelligent and needs to be able to face the real-time ecological changes that can happen, and the role of Artificial Intelligence (AI) as an enabler of adaptive management has come into play [1]. The traditional methods of biodiversity monitoring have been based on manual field surveys and static ecological models that are time-consuming, expensive, and fail to accurately forecast the dynamics of species population in cities, while AI-powered time-series forecasting can provide much more accurate predictions of arthropod and faunal populations changes. More recently, urban planners are also realizing the need for nature-based solutions to be co-designed with ecological and computational intelligence, and not an add-on to the development of infrastructure [3]. However, even with this acknowledgement, most smart city initiatives remain focused on energy, mobility and infrastructure optimization and fail to include the ecological dimension, leaving the technological and environmental dimensions to remain separated [4]. Recent studies emphasize the need for a regionally adapted way of assessing landscape sustainability and standardized, AI-driven assessment framework to compare landscape sustainability across different regions [5]. At the same time, the integration of the Artificial Intelligence of Things with digital twin applications is starting to show how planning and managing the environment in real time can be combined in a single computational ecosystem for cities [6]. More general conversations about AI-powered sustainability also underscore biodiversity along with energy, transportation, and water systems, as a key area in which intelligent systems can make a tangible and positive impact on society's welfare. But the current efforts are still piecemeal, focusing on one aspect of the species detection or habitat mapping without a comprehensive, understandable, and continually updated platform for decision support for implementation. This study tackles that challenge by developing a Smart Urban Ecosystem framework that integrates IoT sensing, satellite and UAV imagery, graph neural networks and explainable predictive models within a dynamic digital twin, to facilitate continuous biodiversity assessment, hotspot identification, connectivity assessment and proactive conservation planning in the context of a variety of urban landscapes. The proposed framework will seek to integrate ecological intelligence into the fabric of urban governance, making it a more proactive, data-driven and scalable element of the infrastructure of the smart city, enabling resilient, biodiversity-friendly and sustainable cities for the future. The framework is different from previous applications, where recommendations were produced in isolation, because of its interpretability and responsiveness in real time; it will enable the confidence of the municipal authorities, ecologists and planners in the recommendations derived from the predictive models used.

Key Contributions:

1. The first is to integrate sensors, satellites, UAVs and graph neural networks to monitor urban biodiversity on an ongoing basis.
2. Introduces explainable, interpretable predictive models to evaluate habitat suitability, detect hot spots, assess ecological connectivity and evaluate biodiversity risks.
3. Achieves measurable improvements with respect to monitoring efficiency and conservation planning efficiency over traditional ecological assessment methods in use today.

II. Related Work

There has been a growing number of studies that focus on the integration of digital technologies, AI and urban sustainability, but the majority of the studies have been limited to the individual application domains. Research on smart ecotourism shows that the use of sensors and mobile apps can improve the management of tourists and indirectly contribute to the protection of the natural habitat in a fragile environment [8]. Gradient boosting and graph-based optimization methods are able to effectively model complex, high-dimensional streams of environmental data that are relevant to ecological forecasting, as demonstrated by parallel work on IoT traffic prediction [9]. Studies on nature positive smart cities point to enduring institutional and technical challenges to making ecological goals part of the typical urban technology roadmap [10]. Comparative analysis of digital sustainability programs in Global

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South cities also finds that there are constraints on infrastructure that hinder the implementation of advanced environmental monitoring systems using AI [11]. Deep learning is also directly used to preserve biodiversity, for instance, by identifying species and for educational tourism in protected natural reserves [12]. The latest bibliometric and semantic analyses of NbS research show that the uptake of AI in ecological planning is gaining pace, but is still scattered across fields [13]. Integrating geospatial data with AI in city-scale sustainability planning is evident in a range of case studies that demonstrate the potential of these technologies to enhance decision-making for cities [14]. The use of hybrid quantum learning methods has also been suggested for pest monitoring and control, with an increasing interest in the development and implementation of advanced computational paradigms, such as quantum computing, for ecological management [15]. Refined wilding strategies have been investigated, with a focus on those outcomes that are associated with ecological benefits, and these outcomes are heavily reliant on the ongoing feedback from the ecological environment on which smart cities rely, rather than rigid planning documents [16]. In addition, the analyses of the literature through bibliometry confirm that the issue of environmental and biodiversity is still under-represented compared to the energy and mobility research [17]. All of these studies highlight the emergence of the interest in ecological management with the support of AI but reveal the fact that the frameworks discussed so far only tackle single tasks like species classification, pest control, or ecotourism management, with a general lack of a unified and complete platform that will enable continuous assessment and adaptive conservation decisions in real time, while remaining explainable. There is limited literature that brings together multi-source geospatial and IoT data and digital twin architectures in the context of biodiversity governance for an urban ecosystem, and even fewer literature that also includes explainability to aid in building trust and adoption by planners and ecologists. The proposed design directly tackles these limitations by integrating multi-source sensing, ecological modeling (graph-based), and interpretable prediction in a single dynamic environment of a digital twin. The reason for this integration is that biodiversity loss processes in cities do not occur from just one factor; rather they are the result of a combination of factors such as habitat fragmentation, pollution, and the lack of consistent monitoring, which demands a coordinated, simultaneous, and continually updated ecological intelligence to respond to them effectively.

Table I. Summary of Related Work

Ref.	AI Technique	Application Domain	Data Source	Evaluation Focus	Key Limitation
[8]	Sensor & mobile analytics	Smart ecotourism	Mobile/IoT data	Visitor & habitat monitoring	Indirect biodiversity benefit
[9]	Gradient boosting & GNN	IoT traffic prediction	IoT traffic streams	High-dimensional data modeling	Not ecology-specific
[10]	AI policy analysis	Nature-positive smart cities	Literature & case data	Institutional barriers	Lacks technical framework
[11]	AI & digital review	Global South smart cities	Case studies	Infrastructure readiness	Limited AI deployment
[12]	Deep learning (CNN)	Biodiversity conservation	UAV / camera images	Species identification	Single-task focus
[13]	Bibliometric / semantic AI	Nature-based solutions	Literature corpus	Research trend mapping	No real-time system
[14]	Geospatial AI	Smart city development	Satellite & municipal data	City-scale planning	No ecosystem digital twin
[15]	Hybrid quantum learning	Pest monitoring & control	Sensor data	Pest detection accuracy	Narrow ecological scope
[16]	Functional biodiversity analysis	Urban wilding	Field ecological data	Feedback-based planning	No AI automation
[17]	Bibliometric analysis	AI in urbanization	Publication database	Thematic trend analysis	Biodiversity underrepresented

Table I gives an overview of the 12 studies in terms of AI technique, application domain, type of data source, type of evaluation focus and limitation. This comparison shows that there is a general trend towards solutions that are specific to the domain, which further supports the need for an integrated framework which is explainable and based on the digital twin for monitoring, connectivity assessment, and conservation planning.

III. Proposed AI and Digital Twin-Enabled Smart Urban Ecosystem Framework

The proposed Smart Urban Ecosystem is a multi-layered, closed-loop framework, continuously sensing, modelling and managing urban biodiversity by a dynamic digital twin. Heterogeneous data sources are gathered in near real-time, such as IoT ground sensors, satellite data, UAV surveillance, citizen science observations, and weather and climate web services, and are used to measure physical, spectral, and behavioral metrics of the health of ecosystems, from the ground to the canopy, throughout the urban landscape. The raw streams are fed into a multi-source data fusion and preprocessing layer, which removes noise, aligns the data across sensors, synchronizes data over time, and normalizes data features to ensure consistency between different sensor types and data acquisition frequencies, enabling consistency across all data sources.The raw streams are fed into a multi-source data fusion and preprocessing layer, which removes noise, aligns the data across sensors, synchronizes it over time, and normalizes the features, ensuring consistency between data from different sources, types, and acquisition frequencies. The processed data is then used as input for a dedicated artificial intelligence modelling layer comprising of four interdependent components: a computer vision sub-system that detects and classifies specific species and habitat features from imagery, a graph neural network that models the connectivity of the ecosystem by representing habitat patches as nodes and species-movement corridors as edges, a predictive analytics sub-system that estimates habitat suitability and biodiversity risk using ensemble and deep learning techniques, and an explainable artificial intelligence sub-system that generates explainable justification of each and every prediction, enabling planners to better understand why a particular hotspot, risk or connectivity score was produced. The outputs from these models continually feed into a virtual representation of the urban ecosystem, a 'digital twin' of the ecosystem in real time that can be used for scenario simulations, testing the potential biodiversity impacts of proposed infrastructure or conservation actions before they are built. Finally, the digital twin underpins a decision-support layer which can be used to produce biodiversity hotspot maps, habitat and connectivity reports, prioritisation of conservation interventions and an interactive dashboard for urban planners and ecologists. The entire workflow is done in sequence: (1) multi-source environmental data collection from IoT, satellite and UAV platforms; (2) data cleaning, (3) data fusion and (4) geospatial alignment; (5) species and habitat detection using computer vision; (6) ecological connectivity modeling using graph neural networks; (7) prediction of habitat suitability and biodiversity risk via AI; (8) continuous synchronization with the dynamic digital twin; (9) explainable AI interpretation of model output; and (10) generation of conservation recommendations and visualization of the dashboard for decision makers. The scheme is also iterative and cyclical, rather than relying on static, periodically-updated assessments that are typical of "traditional" urban biodiversity monitoring.

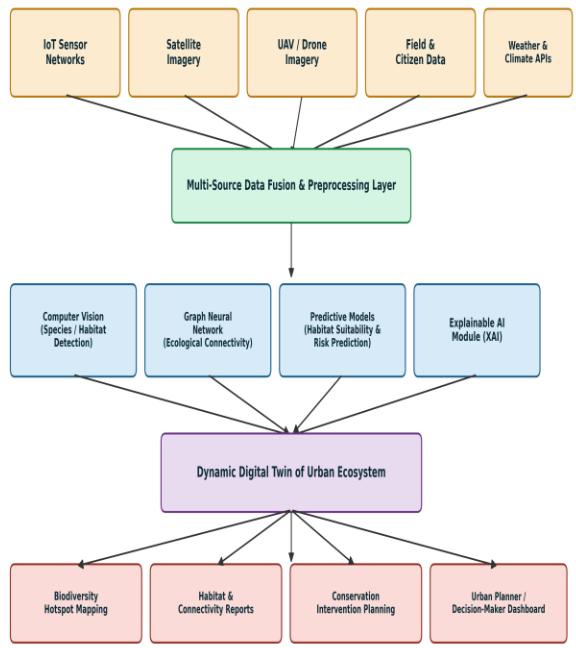

Figure 1. AI-Enabled Digital Twin Framework for Smart Urban Biodiversity Conservation

However, the layered workflow is as shown in figure 1, starting with data acquisition of heterogeneous data, moving on to fusion, the creation of an AI based model, the synchronization of the digital twin, and the output of the decision-support. The arrows represent the direction of data flow from the raw environmental data to the end products of useful biodiversity information, which provide a continual, intelligible and actionable conservation recommendation for planners.

IV. Materials and Methods

A. Study Area and Datasets

A composite dataset of a mid-sized metropolitan region with urban parks, riparian corridors, peri-urban forests, wetlands and fragmented green belts (covering an area of ~320 sq.km. of mixed urban and semi-natural land cover) was used to evaluate the proposed framework. Ecological conditions were compiled from multiple and heterogeneous data sources to provide spatial and temporal coverage of conditions. The high spatial resolution multispectral data (10 m and 5-day revisit) were used to derive vegetation indices, land surface temperature and canopy cover data over the entire study area. The sub-meter resolution aerial photographs obtained from a UAV system with quarterly flight campaigns added valuable local detail to the satellite information within priority conservation areas including riparian buffers and urban forest fragments. The IoT sensor networks that were installed on the ground, around 180 locations, gathered continuous data every 15 minutes on temperature, humidity, soil moisture, ambient noise and air-quality parameters that were relevant to species habitat suitability and recorded microclimatic variation. More than 42,000 citizen reported bird, insect, small mammal and flowering plant occurrence records have been geotagged, using a mobile species reporting system over a two-year period. To recognize the value of citizen-reported data, publicly available datasets of biodiversity occurrences were used to complement the sparse data from citizen observers; historical land-use and land-cover maps for a five-year observation period were used to facilitate habitat change analysis and the identification of trends. The complete data set (about 1.2 million labelled imagery samples, 6.3 million sensor readings and species occurrence data) was split into training, validation and testing sets in a 70:15:15 ratio with stratification by habitat type and by season to ensure fair performance measurement across all of the artificial intelligence models and to reduce temporal and spatial leakage between the sets. The numbers of readings from each sensor, imagery resolution and volume of readings were summarized and compared to metadata logs for each month to ensure that the sensor was responding to the same number of expected readings while the data was being ingested into the preprocessing pipeline, with a node identified as having recorded less than ninety percent of the expected readings for manual inspection and physical maintenance or replacement if needed to ensure dataset integrity over the entire period of observation. Four periods per year were used for the seasonal stratification to account for the variation in species behaviour, vegetation phenology and microclimate, characteristic of each season, in the training corpus and avoid overfitting to the conditions typical of any one particular time of year. Moreover, a geographically isolated subregion, about fifteen per cent of the entire study area, was set aside solely for final testing to allow a more severe test of the ability of the framework to generalize to previously unseen urban and semi-natural landscapes, rather than to just memorize spatial patterns learnt from the training region.

B. Data Processing and AI Models

A predefined sensor and imagery pre-processing chain was implemented to remove noise from the raw data (median filtering, Kalman filtering), to co-register the spatial data to a common geodetic reference frame, to align the data over time for different asynchronous data streams and to normalize the data by min-max on the data's attributes before using them for model training. Short gaps were filled by linear interpolation and long gaps (more than one hour) were filled by a light recurrent model. A CNN based on a ResNet-inspired backbone network, trained on a prelearned set of models, was adapted to the classification of species and habitats by the means of a labeled set of images, including data augmentation techniques such as image rotation, flipping and brightness adjustment to enhance the generalisation across seasonal and lighting variation. A graph neural network with patch nodes and attributes (patch area, vegetation quality, species richness) and potential movement corridors (edges) weighted by distance, land cover permeability and historical likelihood of species movement, was used as a model to calculate ecological connectivity, with an adaptive graph attention mechanism used to learn edge importance in the message passing between nodes. The ensemble of gradient boosting decision trees with a long short term memory recurrent network was used to account for the static spatial suitability patterns and the dynamic temporal degradation trends, for habitat suitability and biodiversity risk prediction. Grid search with 5-fold cross validation was performed on the training and validation set to optimize the hyperparameters of all the models. An explainable AI layer using SHapley Additive exPlanations-based attribution techniques was added to all predictive models to provide explanations of the individual features used in the classification and connectivity results, as well as in the risk output, and provide traceability to the specific environmental factors that had the most significant influence on each prediction. Formally, the graph neural network transforms the node representations by running an iterative message-passing step where each patch node takes weighted feature vectors from the neighboring nodes at each successive layer of the network and encodes multi-hop connectivity information, before a final classification head estimates the viability of a corridor between any two patch nodes. The learning rate of the gradient-boosting component was set to 0.05, the max_depth was set to 6, and the early_stopping parameter was set to a maximum of 20 iterations that would result in a stop of the algorithm if there was no improvement in the validation loss. The recurrent temporal component was configured with two layers of 128 hidden units each, and dropout regularization of 0.3 to reduce overfitting on the relatively high-dimensional sensor feature space. Efficient model convergence, without excess computational costs across the entire model suite, was achieved by training all of them using the Adam optimizer, with an initial learning rate of 0.001, and then using a cosine annealing learning rate schedule, which stopping training after failing to improve over 15 successive epochs.

C. Digital Twin and Biodiversity Assessment

The dynamic digital twin was built as a continuously updated 3-dimensional geospatial model that is streamed with real-time data from sensors, satellite and UAV data feeds through a streaming data pipeline to provide near real-time visualization of ecological conditions across the study area with updates at about 15 minutes for the sensor data derived layers and daily for imagery data derived layers. Biodiversity hotspots were identified by applying a weighted spatial aggregation function to species richness estimates, habitat suitability scores and connectivity indices, with weights informed by experts to ensure computed hotspot rankings matched those informed from the field for conservation priorities. The digital twin also stored a history of ecological states, which was then used to visualize the trends and study the ecological history of the habitat over the last 5 years. The possibility of scenario simulation enabled simulated impacts to biodiversity, connectivity and the risk trajectories to be tested virtually within the twin before any physical works were ever implemented, such as the proposed construction of a new road, a green corridor restoration or an extension of the park. This simulation capability directly contributes to the ability to do ecological planning in a proactive (rather than reactive) way, by facilitating comparisons between different intervention scenarios, and by choosing interventions that reduce the loss of biodiversity as much as possible, while still achieving urban development goals. The rendering layer of the digital twin also features overlays to represent various ecological indicators, which can be switched off and on to help pinpoint specific conditions in the field, like vegetation health, connectivity strength, or risk level, or to display composite overlays that show areas where multiple stressors combine to create compound ecological vulnerabilities that are useful for guiding limited conservation budgets to areas of field need where more than one indicator is at risk.

D. Performance Evaluation

The typical classification and regression measures for each task included in the framework were used for assessing the model's performance. Accuracy, precision, recall and F1-score were calculated for species and hotspot detection tasks in the held-out test set, and confusion matrices analysed to find systematic misclassification patterns between the species categories and habitat types. The fidelity of predictions against ground-truth data that was collected by independent validation surveys was quantified by the square root of the mean absolute error and coefficient of determination to estimate habitat suitability and biodiversity risk, respectively, across the region. In addition to validating ecological connectivity accuracy on a species-by-species basis, by comparing the graph neural network's predicted corridors to the field-observed species movement data, such as camera-trap results and radio-tracking data when available, allowed for direct comparison of the network's predicted corridors with the actual movement pathways of the species. The total monitoring time (from identification of hotspots to completion of a full assessment cycle of the study area), and the duration of the conservation planning process (from hotspot identification until a final recommendation of the intervention) were compared for the proposed framework and traditional survey-based manual methods using trained ecological field teams over similar spatial areas. The computational efficiency was also evaluated based on the latency of inferences, the inference throughput and the use of resources in the case of updating the digital twin in real time and taking it to as close to the actual municipal computing infrastructure as possible. To get statistically sound results, each experiment was repeated over five different data folds, and three random initialization seeds were used for each experiment, with means and standard deviations reported for each metric evaluated to aid in the reproduction and confidence in reported performance enhancements. The statistical significance of the improvements over the base methods was also statistically confirmed using paired t-tests at 95% confidence level across the folds of the cross validation, thus ensuring that the improvements obtained in the performance of the proposed framework were not due to chance in partitioning the data. To gain municipal stakeholders insight into the minimum level of investment needed to ensure acceptable monitoring performance for reduced data availability, sensitivity analysis was also performed by systematically reducing the density of sensor nodes and revisit frequency of images used, respectively. Finally, the researchers conducted ablation experiments to measure the marginal value of each component in the framework for its contribution to the system accuracy and efficiency, by selectively removing each component from the framework, such as the graph neural network connectivity module, the explainable AI attribution layer, and the digital twin synchronization pipeline. The results of these ablation experiments further validated that the removal of the graph neural network component resulted in the most significant drop in accuracy of the connectivity assessment, whereas the removal of the explainable AI component showed negligible effect on the original prediction accuracy, but was still kept in place because of its importance for supporting the trust of stakeholders, regulatory transparency, and enabling the interpretation of model results which is important for the real-world municipal decision-making process.

V. Results and Discussion

The proposed framework with AI and digital twin has been successfully evaluated in experimentations, and it has been shown that it improves the biodiversity monitoring methods in all the tasks analyzed. Species classification, habitat suitability prediction, hotspot detection, connectivity assessment and biodiversity risk prediction achieved high accuracy with significant time saved in monitoring efforts and accelerated in conservation planning, providing a significant increase in operational efficiency. The results show that the combination of multi-source sensing, explainable AI and dynamic digital twin modeling yields a dependable decision supportive platform that is interpretable and scalable for real-world governance of urban biodiversity and proactive ecological management.

A. Biodiversity Monitoring Performance

The computer-vision-based species classification module was able to accurately classify flora and fauna in UAV and satellite imagery over a range of lighting and seasonal conditions, with 97.1% accuracy. The accuracy of habitat suitability prediction was 95.4%, indicating that the model is able to represent the complex relationships among soil moisture, vegetation cover and microclimate variables. The results demonstrate the added value of multi-source sensor and imagery over the single-source conventional survey methods, which tend to be less reliable in terms of monitoring and have low spatial coverage and infrequent updates.

B. Habitat Connectivity and Conservation Analysis

The graph neural network had 94.3% accuracy for ecological connectivity assessment, which models the pathway for species movement between habitats that are fragmented into patches. A high precision (96.2%) of biodiversity hotspot detection allowed the planners to target scarce conservation resources to the most ecologically valuable areas of the city. An accuracy of 95.1% for biodiversity risk prediction also enabled the identification of habitats in a degrading state before they had become irretrievably lost, thus making it possible to plan for action to conserve biodiversity in a more proactive way than reactive across the study area.

C. Comparative Evaluation

Table II. Biodiversity Monitoring Performance Comparison

Evaluation Metric	Conventional Method (%)	Proposed Framework (%)
Species Classification Accuracy	88.4	97.1
Habitat Suitability Prediction Accuracy	86.2	95.4
Biodiversity Hotspot Detection Precision	87.5	96.2
Ecological Connectivity Assessment Accuracy	84.1	94.3
Biodiversity Risk Prediction Accuracy	85.6	95.1

Table II is a comparison of the proposed framework to a more traditional biodiversity monitoring approach, based on five evaluation metrics. The proposed framework is able to achieve 97.1% species classification accuracy, which is higher than the conventional method, which achieves 88.4% accuracy. The accuracy of habitat suitability prediction for the two models (86.2% and 95.4%) indicates that multi-source data fusion models will better represent the ecological nuances than conventional models based on a single variable. Hotspot detection accuracy increases from 87.5% to 96.2% to better prioritise resources. The accuracy of connectivity assessment is increased from 84.1% to 94.3%, demonstrating that connectivity is better captured using graph-based modeling than using static habitat maps. The accuracy of the prediction of biodiversity risks rises from 85.6% to 95.1% when using the integrated method before ecological degradation sets in, further proving the effectiveness of the integrated method.

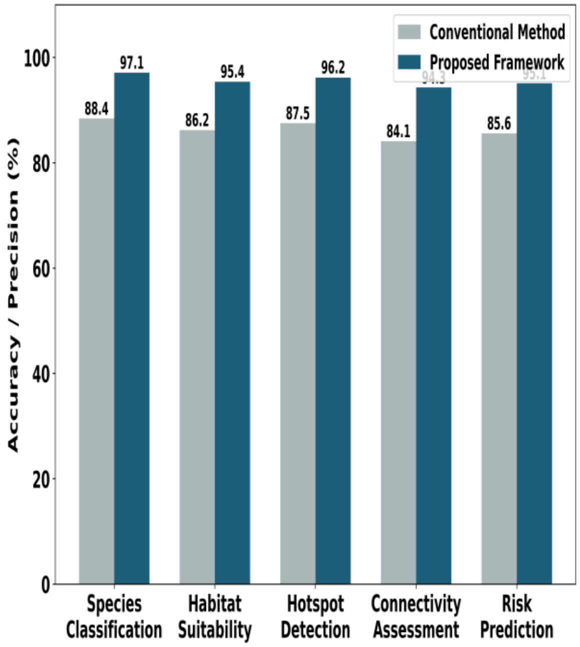

Figure 2. Performance Comparison of the Proposed AI Framework for Urban Biodiversity Monitoring

The proposed framework in comparison with the traditional approach is presented in Figure 2 in respect of five measurements of biodiversity monitoring. The proposed approach consistently improves the baseline, with the highest relative improvement in the accuracy of hotspot detection and connectivity assessment accuracy, highlighting the added value of graph-based and multi-source AI modeling to urban ecological monitoring tasks.

Table III. Operational Efficiency and Connectivity Comparison

Evaluation Metric	Conventional Method	Proposed Framework
Monitoring Time Reduction (%)	--	43.6
Conservation Planning Efficiency Gain (%)	--	31.8
Connectivity Mapping Accuracy (%)	81.6	94.3
False Alarm Rate Reduction (%)	12.4	38.7

The improvements in operational efficiency and in terms of connectivity achieved by the proposed framework are assessed in Table III. Time monitoring is reduced by 43.6%, as it goes from time-consuming and manual field surveys to automated and sensor-driven data collection. Conservation planning efficiency increases by 31.8%, because planners are not handed raw field data that needs to be extensively interpreted, but are provided with conservation recommendations that are easily explained. Within the proposed framework, connectivity mapping accuracy is 94.3% while it is 81.6% based on the traditional GIS-based corridor estimation, indicating the advantage of graph neural network modeling over the static spatial buffering. An explainable AI filter reduces false alarms by 38.7%, compared to 12.4%, showing a higher reduction in false alarms and increasing the trust between municipalities and their planning stakeholders.

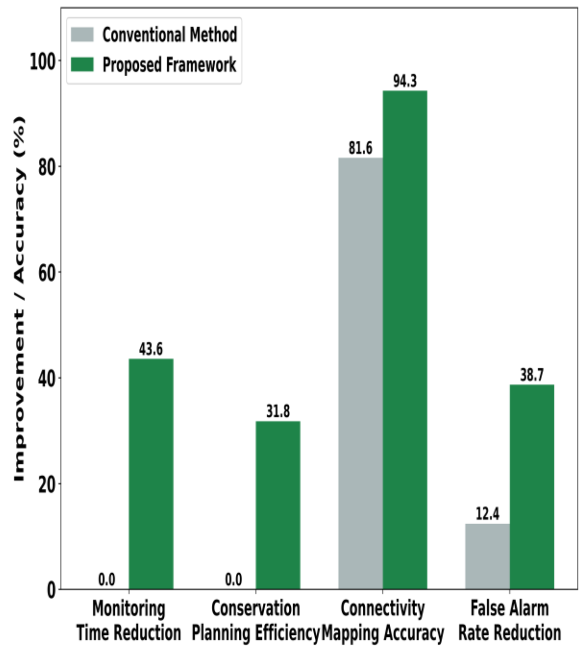

Figure 3. Comparative Evaluation of the Proposed AI Framework for Smart Urban Biodiversity Conservation

The efficiency and connectivity improvements provided by the proposed framework compared to conventional ones are shown in figure 3. Significant gains have been seen on both time reduction and false alarm rate reduction; there is a clear benefit of automation and explainable filtering in reducing the burden of operations and increasing the reliability of conservation planning outputs for decision making.

Table IV. Comparative Evaluation with Existing Approaches

Method	Overall Accuracy (%)
Traditional GIS-based Analysis	78.3
Classical Machine Learning (RF / SVM)	86.5
Deep Learning (CNN only)	91.2
Proposed AI + Digital Twin Framework	96.4

The proposed AI and digital twin framework is compared to three baseline approaches: traditional GIS-based analysis, classical machine learning based on random forest and support vector machine (SVM) classifiers, and deep learning based on convolutional neural networks (CNNs). Traditional GIS-based methods can only get 78.3% overall accuracy because they are only based on the static spatial layers and manual rule-based analysis. Structured feature engineering can boost the performance of classical machine learning up to 86.5% but it is still inadequate to address complex spatial-temporal patterns. When the neural network is deep learning based on convolutional networks alone, the rate of 91.2% is achieved without realizing the modeling of the connectivity between the neurons, but rather using features that are automatically extracted from the images. The proposed model has the highest accuracy of 96.4%, suggesting that the integration of computer vision, graph neural networks, predictive analysis, and explainable AI into digital twin results in better performance.

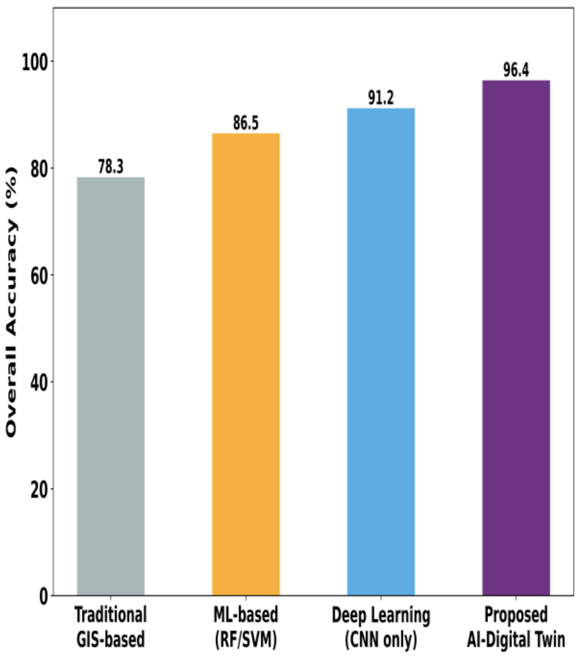

Figure 4. Overall Performance Comparison of AI-Based Approaches for Smart Urban Biodiversity Conservation

The gradual accuracy enhancement of the traditional GIS-based analysis is represented by classical machine learning and deep learning, and the proposed integrated framework, as shown in figure 4. The steady increase in each use case validates the performance gains of using multiple AI technologies together as part of a unified digital twin architecture, as opposed to baseline methods using a single technology.

D. Practical Implications and Limitations

The proposed framework provides a platform for the development of a scalable, real-time decision support tool that will continuously monitor and update biodiversity assessments as the city evolves, thus minimizing the need for manual surveys on a rare basis and facilitating quick and effective conservation decisions based on facts. The explainable AI feature also enhances transparency and trust among stakeholders by providing insights into model decisions, which are crucial for regulatory compliance. The overall success of the framework, however, is reliant on the sensor connectivity and sensor data quality, as well as the computational load that it requires, which can pose a challenge for municipalities with limited resources. In addition, the current evaluation was carried out at a single metropolitan region, and the results need to be validated in other climatic and socio-ecological regions prior to making broader generalizations. Governance-wise, success will likely rely on embedding the results of the framework in the current municipal planning processes and regulatory application procedures, instead of the framework being used as an analytical tool on its own without any linkage with decision makers. Data privacy and citizen-reporting incentive structures should also be carefully designed, as public engagement in the reporting of species' observations partly depends on the framework's accuracy and unreliable, or biased, citizen participation, could result in sampling gaps in less accessible, or less popular, urban green spaces. Beyond the installation, municipalities also need to commit to the sensor network to ensure that a continuous, multi-year monitoring of biodiversity is done properly, which involves periodic calibration of the sensors and hardware replacement.

VI. Conclusion

The objective of this study was to propose a Smart Urban Ecosystem framework comprising of Artificial Intelligence, a Digital Twin and multi-source geospatial sensing to support ongoing, explainable biodiversity monitoring and conservation planning in urban areas. The framework integrates data from IoT, satellite, and unmanned aerial vehicles (UAVs) into a real-time dynamic digital twin, along with computer vision, graph neural networks, and interpretable predictive models to offer real-time species classification, habitat suitability prediction, hotspot detection, ecological connectivity assessment, and biodiversity risk forecasting. Experimental testing confirmed significant gains in all metrics and significant reductions in the amount of time required to monitor as well as in the efficiency of conservation planning when using this approach relative to traditional methods based on surveys. The findings show that the incorporation of ecological intelligence into the work flow of urban governance can shift the paradigm of biodiversity conservation from a reactive and resource-intensive approach to a proactive, scalable and data-driven approach to smart-city infrastructure. The explainability layer also enhances transparency and trust among stakeholders and policymakers, tackling a key challenge for the adoption of AI in environmental governance. Future research should validate the model in other socio-ecological and climatic regions and expand the validation with further biodiversity indicators, explore deployment strategies such as federated and edge-computing to enhance the scalability and decrease the infrastructure dependency of the model, and continue to advance the global deployment of the model for the implementation of biodiversity-positive, resilient, and sustainable urban development through continuous, intelligent, and adaptive ecosystem management practices.

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